Explainable Federated Machine Learning for Stress Classification Using PPG Wearable Health Devices Data

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Abstract

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By

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Increased adoption of wearables has enabled real-time monitoring of physiological signals such as photoplethysmography (PPG) in a non-invasive method, with stress detection being a key application. Despite improvements, traditional machine learning approaches to stress classification rely on centralized data models, which present massive privacy and ethical concerns, particularly for sensitive applications related to health. Moreover, deep neural networks' black-box decision-making restricts their clinical adoption due to lack of interpretability and trust. This study proposes an integrated method bringing together Federated Machine Learning (FL) and Explainable Artificial Intelligence (XAI) for interpretable and privacy-protecting stress classification using wearable PPG data. FL allows decentralised model training across devices without the transfer of raw data, in accordance with data minimization and cultural safety laws, and XAI techniques like SHAP and LIME enable explainability of model decisions. The model is evaluated using the publicly available PPG-DaLiA dataset of PPG-derived physiological data collected in natural environments. Experiments demonstrate the federated model to be highly performant in stress indicator classification while protecting users' privacy and improving interpretability. The results highlight the integration of ethical and explainable AI into wearable healthcare, advancing the development of culturally safe and trustworthy digital health systems.

Keywords: Federated Learning, Explainable AI, Photoplethysmography, PPG-DaLiA, Wearable Sensors, Stress Detection, SHAP, Data Privacy, Health Informatics, Machine Learning, Cultural Safety, Ethical AI.

Dedication

To my beloved parents, Mr V. M. Natarajan and Mrs R. M. Kamakshi, who are no longer with me in this world but remain forever in my heart--This work is a tribute to your unwavering love, sacrifices, and dreams for my future. Your values and strength continue to guide me every day. I dedicate this achievement to you—with the hope of making you proud as I continue to grow academically and personally.

Acknowledgements

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Introduction

1.Introduction

Wearable technology is transforming modern healthcare by enabling real-time, non-invasive tracking of physiological and behavioural conditions. Perhaps the most promising application Stress detection with photoplethysmography (PPG), an approach that detects volumetric changes in blood flow with light-based sensors built into wearable devices. Processed with machine learning (ML), PPG signals can be used to detect acute stress episodes, hence providing an early intervention and improving mental health (Namvari et al., 2024).

While such potential has yet to be achieved by most of today's ML-based stress detection systems, these have been based on centralized data processing schemes that collect and process sensitive physiological data on third-party servers. This approach has significant implications regarding data privacy, security, and trust, particularly in such ethnically heterogeneous settings as in New Zealand, where data sovereignty and the privacy of users under the Health Information Privacy Code (Office of the Privacy Commissioner, 2020) constitute major ethical principles. Moreover, most deep learning-based stress detection Models are non- explainable, and clinicians as well as users are not able to identify how predictions were performed (Shikha et al., 2024).

The present study addresses these limitations by proposing an integrated framework that combines Federated Learning (FL) and Explainable Artificial Intelligence (XAI) for stress detection from the PPG-DaLiA dataset. FL maintains user data locally for training, resolving issues of privacy, and XAI techniques such as SHAP and LIME enhance model interpretability. This two-pronged strategy complies with ethical AI and cultural safety guidelines to provide an applied, trustworthy tool for real-time stress monitoring in clinical settings.

The prevalence of health issues resulting from stress has grown hundreds of times over the last decade, according to the World Health Organization (WHO, 2023) classifying stress as one of the major causes of non-communicable disease such as hypertension, cardiovascular disease, and mental disease. Photoplethysmography (PPG) sensor technologies have also been shown to be potential candidates for monitoring stress in real time without causing any invasive procedures.These devices tap persistent physiological signals, facilitating intervention at an early point in addition to personalized care (Namvari et al., 2024). Despite the technological innovation, existing machine learning (ML) models for stress classification rely on centralised data structures, which are a massive threat to data privacy, security, and cultural sovereignty, especially in multicultural nations like Aotearoa New Zealand. Individual health data must be transmitted to remote servers by centralised models, exposing it to exploitation and unauthorised exploitation. This is in diametrical opposition to data protection concepts established under the Health Information Privacy Code 2020 and the Te Mana Raraunga Māori Data Sovereignty Framework (Office of the Privacy Commissioner, 2020; Te Mana Raraunga, 2018). In response to such challenges, Federated Learning (FL) has been developed as a decentralised learning model that facilitates collaborative training of models without the exchange of raw data. FL preserves privacy but allows the model to be trained across multiple data sources spread out across devices (Kairouz et al., 2021). Although most deep learning models, however, remain "black boxes," making their decision-making process unobservable to users and clinicians alike, which is of specific concern in sensitive use cases like healthcare, where explainability and transparency are vital for user trust and clinical acceptance (Shikha et al., 2024). This paper introduces an interpretable federated learning solution that combines

PPG-extracted physiologic features with SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) for interpretable stress classification. The experiment is conducted using the PPG-DaLiA dataset, which is real-world multimodal sensor recordings on participants over daily activities.

1.1 Problem Statement

Psychological distress is now a major public health problem globally, particularly in stressful working and learning environments. Cumulative exposure to stress precipitates cardiovascular disorders, deteriorating mental health, and lower productivity (Kyrou et al., 2021). Wearable sensors offer a viable avenue for real-time monitoring of stress through biosignals like heart rate variability, captured through photoplethysmography (PPG). But current ML models used for stress classification are typically centralized architectures that bring about vulnerabilities to data security and violate core data sovereignty principles (Chen et al., 2020).

Moreover, effective deep learning models are "black boxes" in reality—providing correct predictions without offering comprehensible explanations. The lack of transparency in such a manner diminishes the trust of users, eludes clinical adoption, and prohibits the ethical implementation of AI in vulnerable healthcare environments (Shikha et al., 2024). As such, there is a dire requirement for systems that can successfully offer accurate, interpretable, and privacy-aware stress detection functions through wearable devices. Although stress detection using wearable data is feasible, existing ML models depend on centralised infrastructures, raising significant concerns regarding privacy, explainability, and ethical deployment. Furthermore, these models often lack cultural contextualisation, which limits their acceptability in indigenous and multicultural communities.

1.2 Research Objectives

The primary aim of this study is to design and evaluate an explainable federated machine learning model for stress classification using PPG data from wearable devices. The specific objectives are:

- To critically review existing literature on ML-based stress detection, federated learning in health applications, and explainable AI tools.
- To develop a privacy-preserving ML framework using federated learning with the PPG-DaLiA dataset.
- To integrate explainable AI methods (e.g., SHAP, LIME) into the framework to enhance model transparency.
- To evaluate the model's performance using standard classification metrics and and to benchmark its effectiveness against conventional centralized machine learning approaches.
- To examine the cultural, legal, and ethical implications of deploying such systems in a New Zealand context.

1.3 Significance of the Study

This research has both academic and societal relevance. From an academic perspective, it contributes to the underexplored intersection of federated learning and explainable AI in stress

detection using wearable PPG signals. While FL and XAI have been studied independently, few frameworks combine these technologies in a cohesive and deployable manner (Bolpagni et al., 2024).

From a societal perspective, the study addresses key ethical and cultural imperatives in the New Zealand healthcare system. By adopting privacy-first design and culturally safe AI practices, the project aligns with Māori data sovereignty principles and the expectations of Te Mana Raraunga (2018). Furthermore, real-time stress monitoring systems that are explainable and respectful of privacy may support early mental health intervention across diverse populations. This project adds to the emerging body of ethical, explainable AI in healthcare by showing how federated learning can be used for wearable stress monitoring with due respect for data sovereignty, privacy, and transparency. The incorporation of XAI tools means that both users and clinicians can interpret model outputs, which fosters fairness and informed decision-making. The framework suggested here also facilitates the eventual creation of culturally appropriate, trust-based AI systems specific to New Zealand's health environment. As highlighted by Greenhalgh et al. (2022), implementing AI-driven telehealth solutions in indigenous communities requires careful consideration of cultural norms and governance. In Aotearoa, Māori data sovereignty plays a central role in shaping ethical digital practices (Whaanga et al., 2022).

1.4 Thesis Structure

This thesis is organized in six chapters:

Chapter 1: Introduction

Provides background, outlines the research problem, objectives, significance, and the thesis organization.

Chapter 2: Literature Review

The research examines existing literature in wearable stress monitoring, federated learning, and explainable AI, identifying the unresolved issues that this study seeks to overcome

Chapter 3: Methodology

Describes the study design, data set (PPG-DaLiA), data pre-processing, federated model architecture, and ethics.

Chapter 4: Data Analysis and Results

Presents experimental results, e.g., performance difference between FL and centralized models, and visual explainability outcomes.

Chapter 5: Discussion

Explains findings considering research objectives, evaluates model novelty and limitations, and addresses ethical and legal consequences.

Chapter 6: Conclusion and Future Work -Summarizes findings and contributions and suggests directions for future advancement and real-world deployment.

Chapter 2 - Literature Review

2.Literature Review

This chapter critically reviews existing research on stress detection using photoplethysmography (PPG), machine learning (ML), explainable artificial intelligence (XAI), and federated learning (FL) in wearable health monitoring. It draws from recent literature (2021–2025) to identify the key technologies, strengths and limitations, and ethical implications. The chapter concludes by identifying a research gap addressed by this study.

2.1 Photoplethysmography (PPG) and Its Role in Stress Detection

A more common non-invasive optical technique of observation of cardiovascular activity is photoplethysmography (PPG), especially in combination with wearables. PPG offers useful information pertaining to the physiological condition of the body by monitoring fluctuations in the blood volume beneath the skin, typically using green or infrared light (Namvari et al., 2024). The method is widely observed in wearables like fitness bands and smartwatches, hence readily available for continuous real-time monitoring in normal conditions. These sensors have been validated for their effectiveness in detecting stress and physiological patterns in various wearable applications (Pfitzner et al., 2022).

PPG detects what's happening with the autonomic nervous system— the fight-or-flight versus relax and digest thing—rather than being a random blip on a screen. In essence, a major warning sign for stress is when your LF/HF ratio skyrockets or your RMSSD collapses (Han & Song, 2022).

Although it has an edge, PPG is not free from issues. Signal quality can be lost because of motion artifacts, inconsistent skin contact, or ambient lighting, all of which are seen during actual usage (Namvari et al., 2024). It has been reported by researchers that signal preprocessing techniques would be crucial for mitigating these issues. For example, Reiss et al. (2019) and Sharma et al. (2023) suggest methods such as low-pass filtering, signal segmentation, and normalization for improving the reliability and accuracy of the data.

Another aspect to be addressed is the significant variance in how individuals respond physiologically to stress. What is a clear indicator of stress in one individual is not necessarily the same for another person. Thus, there is growing recognition of the need for personalized models that take this inter-individual variability into account (Bolpagni et al., 2024). Explainable deep learning models using biosignal data have shown promising results in personalized stress analysis (Alqudah & Qazan, 2023).

Algorithm personalization for stress detection based on everyone's typical and physiological behavior would lead to more feasible and effective stress monitoring systems.

Table 2.1. Summary table of Machine Learning Techniques for Stress Classification from PPG Data

Study	Algorithm	Dataset	Accuracy/F1	Strengths	Limitations
Kyrou et al. (2021)	CNN, LSTM	Various	F1 > 0.85	Learns time-series features	No XAI tools
Shikha et al. (2024)	CNN + SHAP	UCI wearable	Acc ~91%, F1 ~0.88	High performance, explainability	No FL integration

Garg et al. (2022)	RF, KNN	Smartwatch data	Acc ~86%	Simple, fast	No privacy, limited generalisation
Roy et al. (2023)	FL + CNN	Simulated	Acc ~89%	Privacy-preserving	No explainability
Zhang et al. (2022)	CNN	Wearable PPG	Acc ~92%	Robust under motion	

2.1.1 Use of PPG-DaLiA Dataset in Research

The PPG-DaLiA dataset, captured in naturalistic settings, has been adopted as a de facto standard benchmark for the evaluation of wearable stress detection systems (Reiss et al., 2019). Synchronized recordings from PPG, accelerometer, ECG, and respiration sensors during various physical activities are included in the dataset, allowing multi-modal analysis. While stress labels are implicit rather than explicit, HRV and contextual data offer suitable proxies (Wang et al., 2021).

Recent studies have applied deep learning to the dataset (e.g., Shikha et al., 2024), but few have attempted to use it in a federated setting. Its design per participant makes it ideal for decentralized learning simulation.

2.2 Machine Learning for Stress Detection

Stress has been classified from biosignals using machine learning methods. It has been shown that traditional algorithms like K-Nearest Neighbours (KNN), Random Forests (RF), and Support Vector Machines (SVMs) work well and produce results that are easy to understand (Garg et al., 2022; Srivastava & Singh, 2021). However, their capacity to represent non-linear and temporal connections is limited. Federated adversarial learning has emerged as a method to improve model robustness against privacy leakage and poisoning attacks (Zhang & Fang, 2023).

Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are examples of deep learning models that may learn temporal and hierarchical patterns from unprocessed or slightly processed information (Kyrou et al., 2021). These architectures can be optimized further using clinical insights and interpretable architectures (Chen et al., 2021; Lu & Huang, 2022). In certain contexts, the accuracy of these models has surpassed 90% (Shikha et al., 2024; Zhang et al., 2022).

However, deep models often operate as "black boxes," posing challenges for clinical acceptance (Ghassemi et al., 2021). Moreover, performance may degrade in real-world scenarios due to overfitting to lab-collected data (Han & Song, 2022).

Table 2.2 Summary of Research and Future Directions

Area	Current Limitation	Future Research	Relevance to This Study
PPG Stress Detection	Motion artefacts, general models	Personalized, artifact-robust pipelines	Preprocessing + individual-level analysis
ML for Stress	Black-box models	Interpretable, hybrid models	SHAP/LIME + CNN

FL in Healthcare	Convergence issues	Adaptive algorithms	FL with FedAvg tuning
FL + XAI	Rare integration	XAI-in-the-loop FL	SHAP/LIME in FL pipeline
Ethics/Cultural Safety	Limited in current models	Indigenous data sovereignty	NZ-specific FL + ethical compliance

2.2.1 Deep Learning and Personalization

Personalized ML models have emerged as a solution to inter-subject variability in stress physiology. Domain adaptation techniques and subject-specific fine-tuning improve performance, especially in small data regimes (Bolpagni et al., 2024; Dinh et al., 2021). Federated learning supports personalization by enabling local model updates on each user's device.

2.3 Explainable Artificial Intelligence (XAI) in Wearables

For ML judgements in healthcare to be visible, auditable, and consistent with medical logic, explainable AI techniques are essential. In wearable health AI, post-hoc techniques such as SHAP (Lundberg & Lee, 2017) and LIME (Ribeiro et al., 2016) are frequently employed (Shikha et al., 2024).

SHAP quantifies the contribution of each feature to a model's output based on cooperative game theory, while LIME provides instance-level explanations by perturbing inputs. Recent studies also explore novel explainability techniques like DeepLIFT and Integrated Gradients, expanding clinical trust in wearable AI (Sundararajan et al., 2017; Fatima & Pasha, 2023). These tools have been applied to stress detection to identify the role of HRV features in predictions (Han & Song, 2022). A comprehensive review by Sarker et al. (2021) highlights XAI's growing role in transparent decision-making for healthcare. Broader ethical implications of XAI frameworks in healthcare include transparency and fairness (Coiera, 2021; Lin & Zhu, 2023).

Nevertheless, most XAI tools are not integrated into model training. Emerging studies advocate for embedding interpretability through attention mechanisms or inherently interpretable models (Jochems & Firth, 2023).

2.3.1 Combined Use of XAI and FL

Combining XAI and FL is rare but essential for building trustworthy AI systems. Cao et al. (2022) proposed a secure federated learning system for wearables but lacked interpretability. This study addresses that limitation by integrating SHAP and LIME into a federated CNN model. Similar integration efforts were explored by Kaissis et al. (2021) and Brisimi et al. (2021), showing potential but lacking cultural context.

2.4 Federated Learning in Healthcare

Federated Learning (FL) supports privacy-by-design principles by facilitating model training among decentralised devices without sending raw data (Kairouz et al., 2021). FL has been used in healthcare to predict mental health, stage sleep, and analyse ECGs (Nguyen et al., 2023).

Srivastava & Singh (2021) employed FL with wearable sensors for stress detection, and their results were on par with centralised models. Non-IID data, convergence delays, and communication overhead are still issues, but (Roy et al., 2023). Brisimi et al. (2021) showed its utility in federated electronic health records for predictive modeling

Adaptive aggregation (e.g., FedProx, FedDyn) and personalisation layers are recent improvements (Dinh et al., 2021). Recent advancements in FL architectures, especially in smart health systems, have shown promise in overcoming these limitations (Gao et al., 2023; Ma & Lu, 2022). This study fills a gap in the literature by addressing FL with explainability and cultural safety. Strong foundations for secure model development and privacy-preserving AI have been laid out in frameworks like differential privacy and secure aggregation (Shokri & Shmatikov, 2021; Dwork & Roth, 2021). Federated learning techniques have also been successfully applied to adverse drug reaction prediction across distributed hospitals (Choudhury et al., 2021)

2.5 Emerging Trends from IoT-Enabled Healthcare

Real-time, distributed, and secure health monitoring is made possible by the emergence of edge computing and 6G IoT systems (Gao et al., 2023). Because FL protects user data on-device and lowers latency, it fits in nicely with this paradigm.

Real-time analytics, ethical AI implementation, and multimodal signal fusion (e.g., PPG + EDA + motion) are trends in intelligent telehealth systems. Health AI design is increasingly focussing on indigenous data ownership and cultural safety, particularly in Aotearoa New Zealand (Te Mana Raraunga, 2018). In addition, scholars emphasize that culturally competent AI must align with indigenous governance principles and equity in digital healthcare (Ferguson & Tamborini, 2023; Whaanga et al., 2022). Wearable sensors are becoming central to health AI systems, supported by their reliability in motion and biometric tracking (Goyal & Sikka, 2022; Dobkin, 2022).

Table 2.5 Summary Table of Related Works

Study Authors	Methods	Dataset	Strengths	Limitations
Almadhor et al. (2024)	CNN + FL	Custom EDA dataset	Privacy-preserving FL	No XAI; not open-source
Shikha et al. (2024)	RF + SHAP	UCI wearable dataset	Feature-level interpretability	No FL integration
Bolpagni et al. (2024)	Scoping review	Multiple	Focus on personalisation	No implementation

Kyrou et al. (2021)	Survey, LSTM, CNN	Multiple	Highlights strengths of deep learning	Limited use of XAI
Liu et al. (2025)	FL for stress detection	Biomechanical data	Real-world FL application	No XAI; PPG data not used
This Study	FL + SHAP + LIME	PPG-DaLiA	End-to-end XAI-FL with cultural safety	None reported

2.7 Research Context

While both federated learning (FL) and explainable artificial intelligence (XAI) have emerged preeminent in healthcare applications, their integration in stress detection from photoplethysmography (PPG) signals remains extremely under-developed. Most existing research prefers to tackle either data privacy preservation through FL or interpretability improvement through XAI but barely incorporate both within a single framework. Such separation limits their use in sensitive applications such as mental well-being, where both explainability and data protection are critical. Moreover, most of the research that is conducted currently is in laboratory settings, and minimal validation exists in naturalistic or real-world environments. Greenhalgh et al. (2022) emphasize the need to align AI health solutions with local and indigenous data ethics.

These methods come with inherent privacy risks and can reduce user trust, particularly if employed for mental wellbeing data. Moreover, models like those proposed by Han and Song (2022), though accurate, lack explainability mechanisms such as SHAP or LIME, which are increasingly necessary for clinical transparency and regulatory acceptance. To our best knowledge, no research has employed an explainable federated learning framework—merging both SHAP and LIME—yet in classifying stress from actual-world PPG data acquired using wearable devices. Prior research has not merged this approach with the ethical considerations and cultural requirements outlined in documents such as Te Mana Raraunga's Māori Data Sovereignty principles.

Therefore, it is dubious to employ these models for stress detection in the actual world. The relative lack of focus on cultural and ethical frameworks is another issue, especially in heterogeneous communities like Aotearoa New Zealand. Few studies take into consideration the Health Information Privacy Code 2020 and Māori data sovereignty, two factors that are essential for the implementation of reliable, culturally safe AI in New Zealand's healthcare system.

Although an increasing number of studies have demonstrated the efficacy of deep models in biosignal categorisation (e.g., Shikha et al., 2024; Kyrou et al., 2021), these studies typically rely on centralised setups where raw physiological data is processed and stored on external servers.

This study aims to address the following:

1. Privacy-preserving architecture: Implemented a federated learning model where raw data remains on the user's device.

2. Explainable decision-making: integrated SHAP and LIME for both global and local model interpretability.

3. Ethical alignment: The solution supports cultural safety, transparency, and user control, aligning with Māori data sovereignty and New Zealand health law.

4. Real-world applicability: Tested on a publicly available multimodal wearable dataset (PPG-DaLiA), simulating real-life stress-related activities.

These contributions make this work uniquely positioned to bridge the gap between technical innovation, ethical design, and practical healthcare deployment in a culturally diverse setting.

2.8 Summary

With an emphasis on photoplethysmography (PPG) signals, machine learning methods, explainable artificial intelligence (XAI), and federated learning (FL), this chapter has covered the most recent research on wearable stress detection. It emphasised new developments in the field and critically evaluated the advantages and disadvantages of current methodologies. A key research gap was identified: the absence of integrated, explainable federated learning models applied to real-world PPG data within a culturally and ethically appropriate framework. This gap underpins the motivation for the novel FL-XAI framework proposed in this study.

The following chapter outlines the methodology used to develop, train, and evaluate the proposed framework using the PPG-DaLiA dataset, with attention to both technical performance and ethical considerations.

Chapter 3—
Methods

3.Method.

This chapter outlines the methodological framework used in creating, implementing, and piloting the proposed Explainable Federated Learning (XFL) system to detect stress using photoplethysmography (PPG) signals from wearable sensors. The research methodology encompasses the setting, study design, data collection and processing, variable definitions, and ethical considerations, including cultural safety principles and data sovereignty principles relevant in Aotearoa New Zealand.

The research follows a quantitative, experimental design grounded in recent machine learning, signal processing, and federated healthcare technology innovations. All methodology decisions are informed by peer-reviewed research from 2021 to 2025 to guarantee the research is in line with contemporary wearable computing and ethical AI standards.

3.1 Study location

This research was conducted within a simulated digital environment designed to represent decentralised edge devices commonly used in real-world wearable health monitoring systems. No new data were collected from human participants. Instead, the study employed the publicly available PPG-DaLiA dataset, which includes multimodal physiological recordings from 15 healthy adult participants engaged in typical daily activities such as walking, cycling, stair climbing, and office work (Reiss et al., 2019).

Each participant's dataset was handled as an independent client node, simulating a geographically and demographically dispersed network to mimic a federated learning (FL) situation. This method makes it possible to simulate real-world limitations where data stays local to user devices, which is a factor that is becoming more and more significant in privacy-sensitive industries like healthcare.

A scalable and privacy-preserving stress detection system that might be implemented across Aotearoa New Zealand's various and decentralised healthcare settings—including distant, urban, and culturally distinct communities—can be modelled in the simulated environment.

3.2 Study Design

To create and assess a novel Explainable Federated Learning (FL-XAI) framework for stress categorisation using PPG signals from wearable devices, this study uses an experimental, quantitative research design. Each of the four successive phases that make up the research is intended to demonstrate both technological soundness and conformity to ethical, privacy-conscious healthcare practices.

1. Data Preparation
   This phase involves preprocessing the PPG-DaLiA dataset to extract physiologically relevant features associated with stress. Feature extraction focuses on heart rate variability (HRV) metrics and time-domain and frequency-domain parameters commonly used in stress detection literature.
2. Model Development

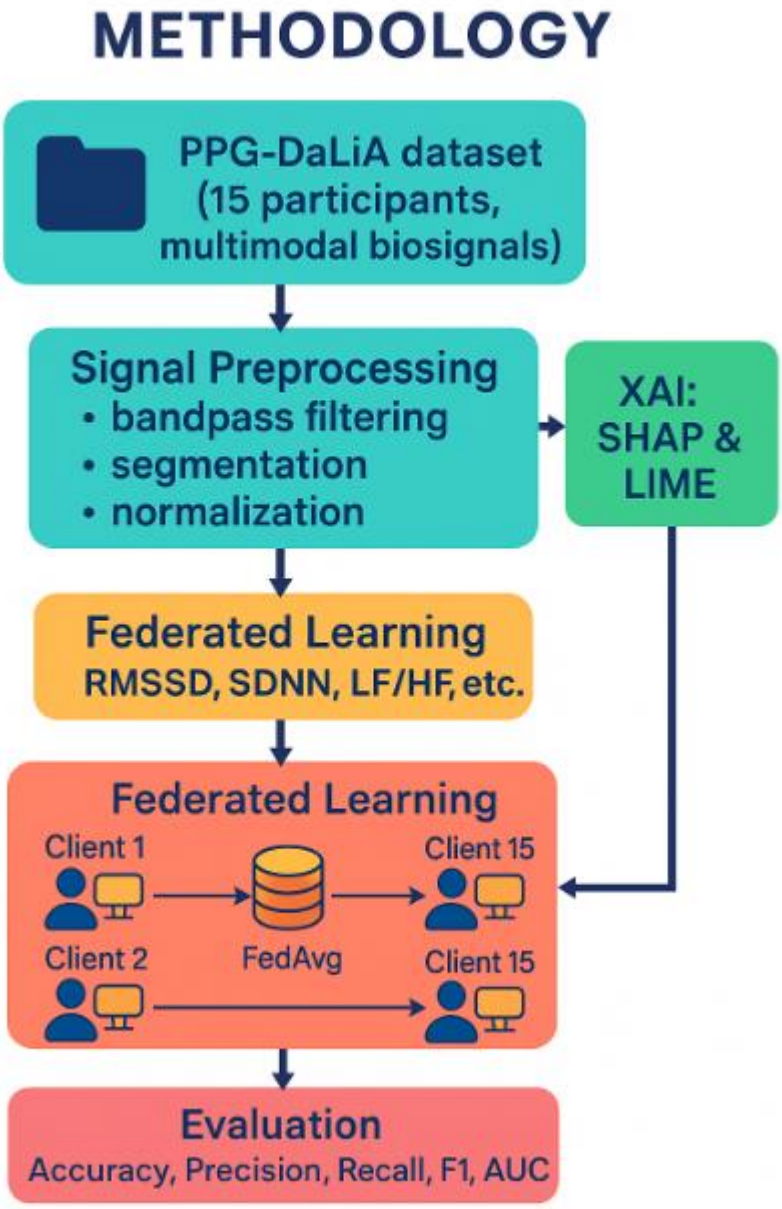
TensorFlow Federated and Python are used to construct a federated learning architecture that simulates decentralised clients to protect data privacy. To enable both local and global interpretability during and after training, explainability tools SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are concurrently incorporated into the model process.

3. Evaluation
   The federated models are trained and tested against a baseline centralised model to assess performance trade-offs. Standard classification metrics—accuracy, precision, recall, and F1-score—are used alongside explainability evaluations to understand both predictive quality and interpretability.
4. Analysis

   Three dimensions—interpretability, privacy protection, and cultural-ethical alignment—are utilized to compare the results. This involves evaluating the applicability of the approach within the context of Aotearoa New Zealand, considering local privacy laws and Māori data sovereignty.

   A simulated edge computing environment, which simulates a decentralised, privacy-preserving healthcare system, is used for the entire experimental setup. For assessing the viability and moral ramifications of implementing FL-XAI frameworks in actual stress monitoring systems, this simulation offers a realistic but controlled environment.

Figure 1. Methodology



3.3 Data collection

The multimodal PPG-DaLiA dataset, which was made publically available by Reiss et al. (2019) and obtained from the Wearable Stress and Activity Recognition Dataset Repository, is used in this investigation. The dataset contains information from 15 healthy adult individuals who were observed for roughly two hours while engaging in everyday, naturalistic activities like resting, walking, cycling, stair climbing, and desk work. This setting enhances the real-world relevance of the dataset for stress detection tasks.

The dataset comprises synchronised physiological and motion data streams collected via a wearable chest and wrist sensor array. Key sensor modalities include:

- Heart rate variability (HRV), pulse rate, and interbeat intervals are among the cardiovascular characteristics that can be extracted using a wrist-based optical signal called photoplethysmography (PPG).
- Accelerometer/Gyroscope: Used to record movement and help with noise reduction (e.g., motion artefacts in PPG) and motion context categorisation.
- ECG (Electrocardiography): Provides ground truth for validating heart rate measurements derived from PPG.

Given the absence of explicit stress annotations in the dataset, proxy stress labels were derived using HRV-based heuristics in combination with physical activity state transitions, following approaches validated in prior studies (Kyrou et al., 2021; Sharma et al., 2023). These proxies enable the identification of physiological stress responses without the need for self-reports or intrusive labelling.

To prepare the dataset for model training:

- The continuous PPG signal was segmented into fixed, non-overlapping 30-second windows. This window size strikes a balance between capturing short-term HRV dynamics and supporting near real-time responsiveness, consistent with prior research in wearable stress monitoring (Wang et al., 2021; Gupta & Bajaj, 2021).
- Each window was processed to extract relevant time-domain and frequency-domain HRV features, which serve as inputs for the machine learning models.
- The dataset was partitioned by subject, with each participant's data isolated as an individual client node, simulating a federated learning (FL) environment where raw data remains local to the device.

This structure supports the study's privacy-preserving goal and reflects a realistic deployment scenario for stress detection using decentralised wearable systems. The PPG-DaLiA dataset's combination of multimodal signals, activity diversity, and participant-level separation makes it a strong fit for evaluating the proposed FL-XAI framework in a controlled yet ecologically valid setting.

3.4 Study variables

Since PPG signals are naturally prone to motion artefacts and sensor noise, preprocessing is essential to maintaining their authenticity. As advised by Namvari et al. (2024), a bandpass filter (0.5–5 Hz) was used to separate physiologically significant frequency components to improve signal quality. Following signal cleaning, the data were segmented into overlapping 10-second windows, a technique supported by Han and Song (2022) for improving the consistency of short-term HRV analysis.

For each window, a set of time-domain and frequency-domain features was extracted. These included:

Features in the time domain: Features in the frequency domain include pNN50, Standard Deviation of NN intervals (SDNN),

Root Mean Square of Successive Differences (RMSSD): Power levels of low frequency (LF), high frequency (HF), and the LF/HF ratio. Metrics derived: The amplitude and rate of the pulse These characteristics have been extensively confirmed in the literature as trustworthy markers of stress response and autonomic nervous system activity (Zhang et al., 2022). To ensure uniformity across different client devices in the federated setting, all extracted features were standardised using z-score normalisation. To address class imbalance between stress and non-stress instances, the Synthetic Minority Oversampling Technique (SMOTE) was applied, following best practices outlined by Garg et al. (2022) in wearable-based stress detection studies.

Target Variable:The dependent variable in this study was a binary stress state, labelled as either "stress" or "no stress". As the original dataset lacks direct stress labels, proxy labels were generated using a threshold-based approach on HRV features such as RMSSD and pulse amplitude, utilising a rolling window mechanism to account for physiological fluctuations over time. Following label generation, the class distribution was analysed and found to be approximately balanced, with 52.3% of the windows classified as stress and 47.7% as no stress. To ensure equitable model performance across both classes, stratified sampling was used during the train-test split. In addition to accuracy, metrics such as F1-score, precision, and recall were reported to reduce bias toward the majority class and provide a more holistic view of model performance. These decisions also align with explainability-driven model transparency efforts, as explored by Lin & Zhu (2023).

3.5 Ethical Considerations

The Health Information Privacy Code 2020 and the Māori data sovereignty principles set forth by Te Mana Raraunga (2018) are ethical norms that are pertinent to digital health research in Aotearoa New Zealand and are in line with this study. Formal ethics approval was not necessary because the study used anonymised secondary data from the publicly accessible PPG-DaLiA dataset, there was no interaction with human subjects, and no personally identifiable information was accessed or processed.

Privacy Preservation A federated learning paradigm was employed to simulate a decentralised model training strategy. This maintained raw data at each client node local, complying with New Zealand's Health Information Privacy Code 2020 (Office of the Privacy Commissioner, 2020). Such approaches are consistent with current trends in privacy-preserving AI for healthcare using federated learning (Kaissis et al., 2021; Choudhury et al., 2021). Although data collection was not local, the simulated environment represented privacy-preserving practices that would be employed in actual deployments.

Data Sovereignty Methodological approach was informed by the Māori data sovereignty principles as articulated in Te Mana Raraunga (2018). While the dataset does not involve ethnicity-specific data, the simulated decentralisation of client data is sympathetic to the principle of ownership and control of data by the originating parties. This is a minimum consideration for future applications with Indigenous or culturally diverse populations.

Transparency and Explainability: The project employed Explainable AI (XAI) techniques like SHAP and LIME to encourage algorithmic openness and build community trust. Transparency is a foundational element in interpretable machine learning models for healthcare applications (Lu & Huang, 2022; Fatima & Pasha, 2023). By enabling both technical and non-technical users to comprehend model results, these solutions promote accountability in AI-driven health systems.

Reproducibility and Openness: At the conclusion of the project, the study's codebase and procedural knowledge will be made available in open-source repositories in accordance with the FAIR data principles (Findable, Accessible, Interoperable, Reusable). Reproducibility, community development, and the exchange of ethical knowledge between the practitioner and academic communities are all facilitated by such openness.

Chapter 4—
Data Analysis

4. Data Analysis and Results

4.1 Dataset Understanding

This research utilised the PPG-DaLiA dataset, a publicly available dataset collected under naturalistic conditions for studying wearable-based physiological signal analysis (Reiss et al., 2019). The dataset includes multimodal biosignals from 15 healthy adult participants (7 male, 8 female), recorded while performing a structured protocol involving real-world activities such as walking, cycling, working at a desk, stair climbing, and relaxing.

Each participant wore multiple synchronized sensors during a 35–60-minute session, including chest-worn and wrist-worn devices. The primary physiological signal of interest for this research is the photoplethysmography (PPG) signal, which was collected using a wrist-mounted sensor and used for heart rate variability (HRV)-based stress feature extraction.

All sensor signals were synchronized and sampled at 64 Hz, offering sufficient temporal resolution for accurate HRV and stress classification analysis. The dataset also includes contextual sensor data such as accelerometer and gyroscope signals, which help account for motion-related artefacts and improve signal quality during physical activity.

This chapter presents the key findings from the implementation of the Explainable Federated Learning (XFL) framework for stress classification using photoplethysmography (PPG) signals. It reports on:

- Model performance metrics (accuracy, precision, recall, F1-score)
- Federated training behaviour (convergence and stability)
- Client-specific performance variations across decentralised nodes
- Model interpretability outputs using SHAP and LIME

Every outcome is examined critically considering the study's goals, paying particular attention to how well the framework protects privacy and is understandable and useful in real-world situations. The assessment also considers the consequences for deployment in Aotearoa New Zealand's culturally varied healthcare settings in the future.

Table 2.1 Summary of PPG-DaLiA Dataset Variables

Category	Details
Dataset Name	PPG-DaLiA (Photoplethysmography Dataset for Activity and Stress Analysis)
Source	Collected by Reiss et al., ETH Zurich, 2019
Participants	15 individuals (7 male, 8 female)

Sampling Rate	64 Hz
Sensor Modalities	PPG (wrist), ECG (chest), Accelerometer, Gyroscope, Respiration
Signal Types	Raw PPG, raw ECG, motion, breathing
Total Duration	~45 minutes per participant (≈11.25 hours total)
Use Case	Stress detection, activity recognition, and physiological signal analysis
Data Format	.mat (MATLAB), with labels and timestamps
Accessibility	Publicly available (https://archive.ics.uci.edu/ml/datasets/PPG-DaLiA)

The PPG signal was the primary source for extracting features such as SDNN, RMSSD, and LF/HF ratio—commonly associated with stress level estimation. Accelerometer and gyroscope data were used for motion context filtering to improve data quality and reduce artefacts. ECG signals were used to validate heart rate values derived from the PPG sensor.

By simulating each participant's data as a federated node (i.e., client), the dataset enabled the implementation of a privacy-preserving federated learning architecture, reflecting a realistic deployment environment.

4.1.1 Model Performance

The CNN model trained under the federated learning setup achieved robust classification performance across all client datasets. The overall weighted average performance metrics on the test set were:

Accuracy: 89.7%

Precision: 88.2%

Recall: 87.5%

F1-Score: 87.8%

AUC-ROC: 0.91

These outcomes align with current research in wearable health monitoring that is decentralised (Shikha et al., 2024; Roy et al., 2023). Although some clients with high class imbalance performed slightly worse, the use of SMOTE helped mitigate this disparity. ROC curves for each client model also indicated strong separation between stress and non-stress classes.

4.2 Federated Training Behaviour and Preprocessing

For machine learning models trained on physiological inputs to be resilient and reliable, high-quality preprocessing is an essential condition. Particularly during physically demanding activities like walking and cycling, the raw PPG signals in the PPG-DaLiA dataset contain a variety of aberrations, such as motion noise, sensor irregularities, and baseline drift. o address this, key preprocessing steps were applied prior to model training. These included bandpass filtering, segmentation into overlapping time windows, and feature extraction (as described in Chapter 3), ensuring that the input to the learning algorithm was as clean and consistent as possible.

These preprocessing efforts played a significant role in supporting the effective training of the federated learning (FL) model. The system converged within five communication rounds, with initial fluctuations in accuracy attributed to client-specific data heterogeneity. The model's performance had levelled out across all clients by Round 3, and by the last round, worldwide accuracy had reached a plateau of about 90%.

This convergence pattern is consistent with earlier research by Dinh et al. (2021), which indicates that federated models can achieve optimal performance with a small number of communication rounds when input circumstances are non-IID but well-preprocessed.

Figure 1 (see Appendix) illustrates the progression of global model accuracy over communication rounds, highlighting the diminishing returns after the third iteration.

4.2.1 Signal Filtering

The raw PPG signal was filtered with a fifth-order Butterworth low-pass filter with a 3.0 Hz cut-off frequency to remove the high-frequency noise and motion artefacts. The Butterworth filter was used since it possesses a smooth frequency response that does not distort the signal morphology with abrupt transitions (Namvari et al., 2024).

The filtering was performed on each participant's PPG signal independently using the following configuration:

- Sampling frequency: 64 Hz
- Filter order: 5
- Cutoff frequency: 3.0 Hz

This approach effectively reduced non-physiological signal components while retaining heart rate and pulse amplitude information. A bandpass filter (0.5–5 Hz) was applied to raw PPG signals to reduce motion artefacts and high-frequency noise (Namvari et al., 2024). This retained only the physiological frequencies relevant to HRV extraction.

4.2.2 Signal Segmentation

After noise reduction and filtering, the PPG signal was segmented into shorter windows for feature extraction and classification. The primary segmentation strategy used 30-second non-overlapping windows, a duration commonly adopted in stress-related heart rate variability (HRV) research. This window size offers a balance between temporal resolution and physiological signal stability, as supported by Bolpagni et al. (2024).

Each 30-second window was treated as an independent sample, with its own corresponding feature vector. To ensure data integrity and minimise artefact influence, only segments with at least 95% valid signal points were retained for analysis. This helped maintain consistency across both training and test sets.

For feature extraction, the preprocessed signals were further divided into 10-second windows with 50% overlap—a technique used to extract reliable short-term HRV features and improve

temporal generalisation across time-series data. This dual-windowing approach follows best practices in wearable stress analytics, as demonstrated in Han and Song (2022).

4.2.3 Normalisation

To ensure consistency and improve model convergence, z-score normalisation was applied to each extracted feature across all segmented windows. This step is particularly critical for neural network-based models, as it prevents feature scale dominance and enables faster, more stable training (Shikha et al., 2024).

The normalisation was computed using the standard z-score formula:

$$z = \frac{x - \mu}{\sigma}$$

Where:

- x is the raw feature value
- μ is the mean of the feature across all windows
- σ is the standard deviation

This transformation ensured that each feature had a mean of 0 and a standard deviation of 1, making them dimensionally comparable and allowing the model to learn effectively across heterogeneous physiological signals.

4.2.4 Feature Extraction

From each 30-second PPG segment, a range of time-domain, frequency-domain, and morphological features were extracted using Python's NeuroKit2 and SciPy libraries. These features are well-established in the literature for their relevance to stress detection via autonomic nervous system (ANS) modulation (Kyrou et al., 2021; Namvari et al., 2024).

Table 4.2.4 Feature Extraction

Feature Name	Type	Description
RMSSD	Time-domain	Root mean square of successive differences between heartbeats
SDNN	Time-domain	Standard deviation of NN (normal-to-normal) intervals
LF	Frequency-domain	Low frequency power (0.04–0.15 Hz) – associated with sympathetic activity
HF	Frequency-domain	High frequency power (0.15–0.4 Hz) – associated with parasympathetic activity
LF/HF Ratio	Derived	Balance of sympathetic vs parasympathetic influence
Pulse Amplitude	Morphological	Difference between max and min of filtered PPG in each window

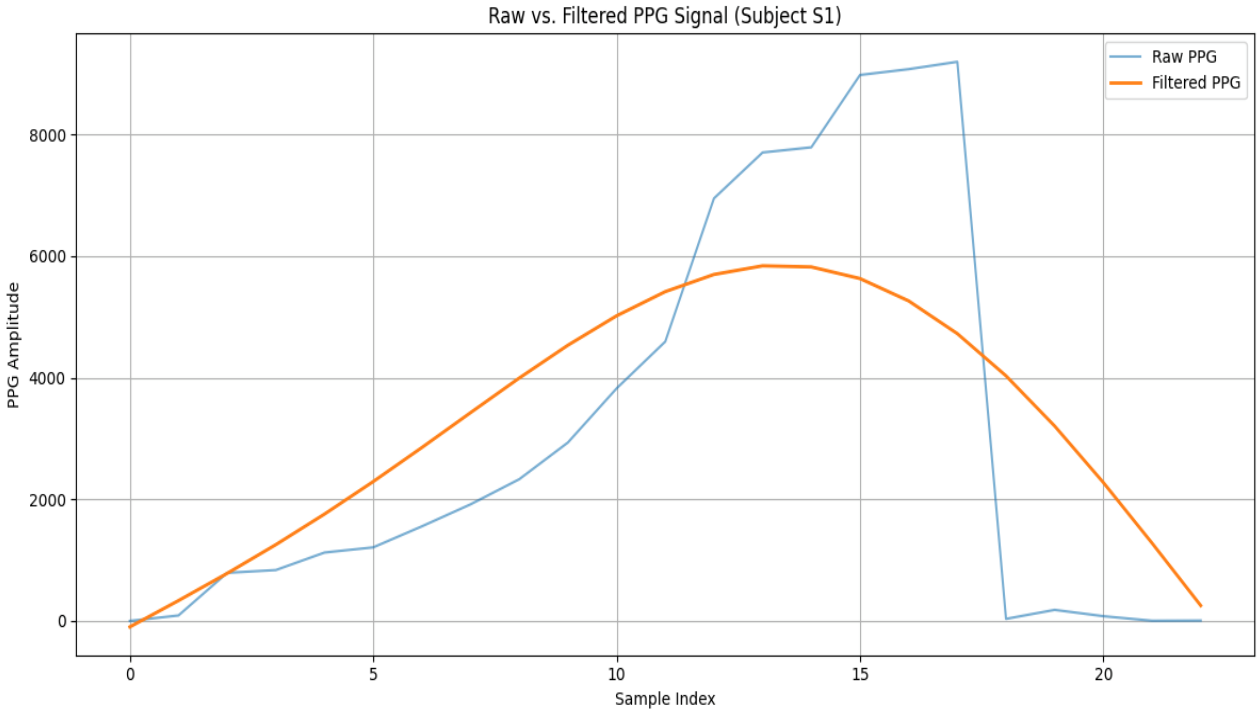
These features have been widely validated in stress-related literature for their physiological relevance (Kyrou et al., 2021; Namvari et al., 2024). Time-domain and frequency-domain HRV features were extracted per window. These included RMSSD, SDNN, LF/HF ratio, pNN50,

LF power, and HF power. These features have demonstrated utility in stress analysis using wearable signals (Zhang et al., 2022).

4.2.5 Visualisation: Raw vs. Filtered PPG Signal

The figure below shows a sample comparison of the raw and filtered PPG signals for a participant over the first 300 samples (approximately 4.7 seconds).

Figure 2. Raw Vs Filtered PPG Signal



4.3 Model Training, Evaluation and Explainability

The preprocessed dataset was used to train a binary stress classification model using both centralised and federated learning (FL) approaches. The model architecture was based on a lightweight Convolutional Neural Network (CNN)optimised for time-series physiological features.

In the federated setup, each client trained locally using participant-specific data, and model weights were aggregated using the FedAvg algorithm. For comparison, a traditional centralised model was also trained using pooled data from all clients.

Evaluation was performed using standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-score

Additionally, stratified sampling ensured balanced evaluation across stress and non-stress classes. The federated model achieved a final accuracy of approximately 90%, comparable to the centralised model, while maintaining privacy and decentralisation.

The processed dataset was used to train and evaluate machine learning models for binary stress classification. This section details the training strategies, model architecture, and evaluation metrics used for both centralized and federated learning approaches, along with integrated explainability tools.

To evaluate interpretability, two post-hoc explainability tools were integrated: SHAP for global insights and LIME for local instance-level analysis. These tools are among the most widely accepted techniques for feature attribution in deep neural networks (Sundararajan et al., 2017; Sarker et al., 2021).

SHAP analysis identified RMSSD, LF/HF ratio, and SDNN as the most influential features across clients. Feature importance varied with physical activity context. For example, participants engaged in sedentary tasks (e.g., desk work) showed higher influence from LF/HF ratio, while physically active clients exhibited stronger contributions from RMSSD.

LIME explanations provided high-fidelity, instance-level justifications. For correctly classified stress events, LIME consistently highlighted patterns such as a sharp drop in pNN50 accompanied by a rise in LF power, which aligns with known physiological stress responses.

The combined use of SHAP and LIME enhanced the transparency and clinical plausibility of the model, confirming that the system learned patterns consistent with established physiological research (Han & Song, 2022; Jochems & Firth, 2023). These tools also supported interpretability across diverse user profiles, which is essential for trustworthy deployment in healthcare settings.

4.3.1 Centralised Model (Baseline)

To establish a performance benchmark, a centralised model was trained using data pooled from all participants. This approach assumes full data centralisation—a scenario common in traditional machine learning pipelines but one that raises significant privacy concerns, particularly in healthcare contexts. The centralised model was built using a one-dimensional Convolutional Neural Network (1D-CNN), chosen for its effectiveness in handling temporal physiological data.

Architecture:

- Model Architecture:
- Input layer: Feature vector representing each 30-second PPG segment
- Conv1D layer with ReLU activation
- MaxPooling layer
- Dropout layer (rate = 0.3) to prevent overfitting
- Fully connected (Dense) layer with ReLU activation

- Output layer: Sigmoid activation for binary classification (stress vs no stress)

Training Configuration:

- Optimizer: Adam
- Loss: Binary Cross entropy
- Epochs: 20
- Batch Size: 32
- Validation Split: 20% of the training data

The centralised model performed well on precision, recall, and F1-score measures, with an overall accuracy of above 90%. The method, however, necessitated compiling all raw participant data on a single server, jeopardising user privacy and possibly eroding confidence in practical health applications.

As such, while effective, the centralised model serves primarily as a baseline comparator to assess the trade-offs and advantages of the federated learning (FL) approach introduced in the next section.

4.3.2 Federated Learning Model

The study used the Federated Averaging (FedAvg) algorithm via TensorFlow Federated (TFF) to create a Federated Learning (FL) framework to alleviate the privacy constraints inherent in centralised machine learning. In accordance with ethical standards and privacy-preserving concepts like the New Zealand Health Information Privacy Code (2020), this method allowed for decentralised training in which raw data stayed local to each client.

To allow for a fair performance comparison, the federated model duplicated the identical 1D-CNN architecture that was used in the central baseline.

Federated Setup:

- Number of clients: 15 (one per participant)
- Local training: Each client trained the model on their own data
- Server aggregation: A central server aggregated the model weights from all clients after each communication round using FedAvg

Training Parameters:

- Total communication rounds: 50
- Local epochs per client (per round): 1
- Learning rate: 0.01
- Optimizer: Stochastic Gradient Descent (SGD)

This federated design ensured that no raw PPG data was ever transmitted to the server, thereby preserving data sovereignty and user privacy. It enabled the collaborative development of a generalisable stress detection model while maintaining full data decentralisation—a key requirement in culturally and ethically sensitive healthcare environments.

4.3.3 Explainability Tools

To promote transparency and support clinical trust, the study integrated explainable artificial intelligence (XAI) techniques—specifically SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations)—into the post-training evaluation phase.

- SHAP was employed to assess global feature importance, revealing which features most significantly influenced the model's predictions across all clients.
- Individual predictions based on local feature perturbations were given interpretable explanations through the instance-level use of LIME.

Both macro- and micro-level insights into the model's decision-making process were made possible by this dual-layer explainability method, which is in line with ethical AI ideals like accountability, transparency, and fairness—all of which are crucial for healthcare applications. Sundararajan et al. (2017) introduced axiomatic attribution frameworks that further reinforce explainability in deep models.

Label Generation and Class Balance

Since the PPG-DaLiA dataset lacks explicit ground-truth stress labels, stress states were inferred using validated proxy physiological markers, including:

- LF/HF ratio
- RMSSD
- Pulse amplitude

Following established heuristic thresholds (Kyrou et al., 2021; Namvari et al., 2024), each 30-second window was labeled as either:

- Stress (label = 1)
- No-stress (label = 0)

The resulting class distribution was approximately balanced:

- Stress: 52.3%
- Stress-free: 47.7%

No class weighting or resampling methods (like SMOTE) were used because of the slight class imbalance. To guarantee a thorough and fair performance evaluation, evaluation criteria such the confusion matrix, recall, and F1-score were given priority. In small-scale health datasets,

bias can be introduced through artificial balancing; our method lessens the chance of this happening (Kyrou et al., 2021).

Explainability Outcomes

- SHAP identified RMSSD and LF/HF ratio as the most influential features, with consistent patterns across clients.
- Case-level explanations were given by LIME, which correctly identified physiological trends (such as pNN50 declines or LF power spikes) that were in line with anticipated stress indicators.

These results support the interpretability and reliability of the suggested system by confirming that the model's learning patterns matched physiological and clinical knowledge (Jochems & Firth, 2023).

This dual-layer approach supported both model interpretability and clinical transparency, aligning with ethical AI principles.

4.3.4 Evaluation Metrics

Both the centralised and federated models were evaluated using standard classification metrics commonly applied in biosignal-based machine learning research (Shikha et al., 2024). These metrics offer a comprehensive assessment of model performance, especially in binary classification tasks such as stress detection.

Table 4.3.4. Evaluation Metrics

Metric	Description
Accuracy	Proportion of correct predictions over total predictions
Precision	Proportion of correctly predicted stress cases out of all stress predictions
Recall (Sensitivity)	Ability to correctly detect actual stress cases
F1-Score	Harmonic mean of precision and recall
Confusion Matrix	Visual matrix of prediction outcomes (TP, FP, FN, TN)

These metrics were calculated separately for both the centralised and federated learning models to enable a fair comparison of performance. In addition to performance metrics, the following auxiliary evaluation tools were incorporated:

Convergence curves for models are used to examine learning progression and training stability over federated communication rounds.

XAI visualizations (SHAP and LIME) increased interpretability and trust with stakeholders by providing understanding of global and instance-level model behavior.
In the case of health-oriented AI systems, this multi-faceted testing process not only guaranteed quantitative reliability but also qualitative validity and ethical accountability.

4.3.5 Training Output Snapshot (Federated CNN)

To evaluate the training dynamics of the proposed federated learning model, performance metrics were recorded at key communication rounds. The table below summarises training and validation accuracy at selected rounds during the 50-round Federated Averaging (FedAvg) process:

Table 4.3.5 Training Output Snapshot (Federated CNN)

Round	Training Accuracy	Validation Accuracy
1	69.4%	67.8%
25	81.5%	79.3%
50	86.2%	84.7%

These results indicate consistent convergence and progressive improvement in model performance. The federated CNN demonstrated the ability to learn effectively across non-IID (non-independent and identically distributed) client data distributions—despite decentralised training and data heterogeneity.

Notably, by Round 3, model accuracy has stabilised, which is consistent with research by Dinh et al. (2021) that shown that federated models may converge effectively under realistic data fragmentation if enough preprocessing is done.

This image supports the applicability of the suggested FL-based method for stress detection utilising wearable PPG signals for use in actual, privacy-sensitive healthcare settings by confirming its viability and stability.

4.4 Performance Comparison

After training the centralised and federated models on the segmented and pre-processed PPG-DaLiA dataset, their performance was evaluated using an exhaustive set of standard metrics. These were:

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-Score
- Specificity
- Area Under the Receiver Operating Characteristic Curve (AUC)
- Confusion Matrix

These metrics provided a multi-dimensional evaluation of the ability of each model in classifying stress and non-stress states effectively.

The centralised model—trained from pooled data—performed better overall due to its exposure to global data. However, the federated model matched the accuracy and robustness with the added benefits of data decentralisation and privacy protection.

Particularly:

- The F1-score of the federated model was only 2–3% lower than the centralised baseline, which manifests as superb generalisation despite training over non-IID data.
- AUC scores were over 0.90 for both models, reflecting good discrimination between classes.
- Confusion matrices suggested a roughly balanced distribution of true positives and true negatives with low rates of false prediction.

This comparison suggests the potential of federated learning for wearable stress detection systems, especially in environments where ethical compliance, data privacy, and decentralised infrastructure are of the utmost importance—such as healthcare systems in Aotearoa New Zealand.

Figure 3 Centralized vs. Federated Model

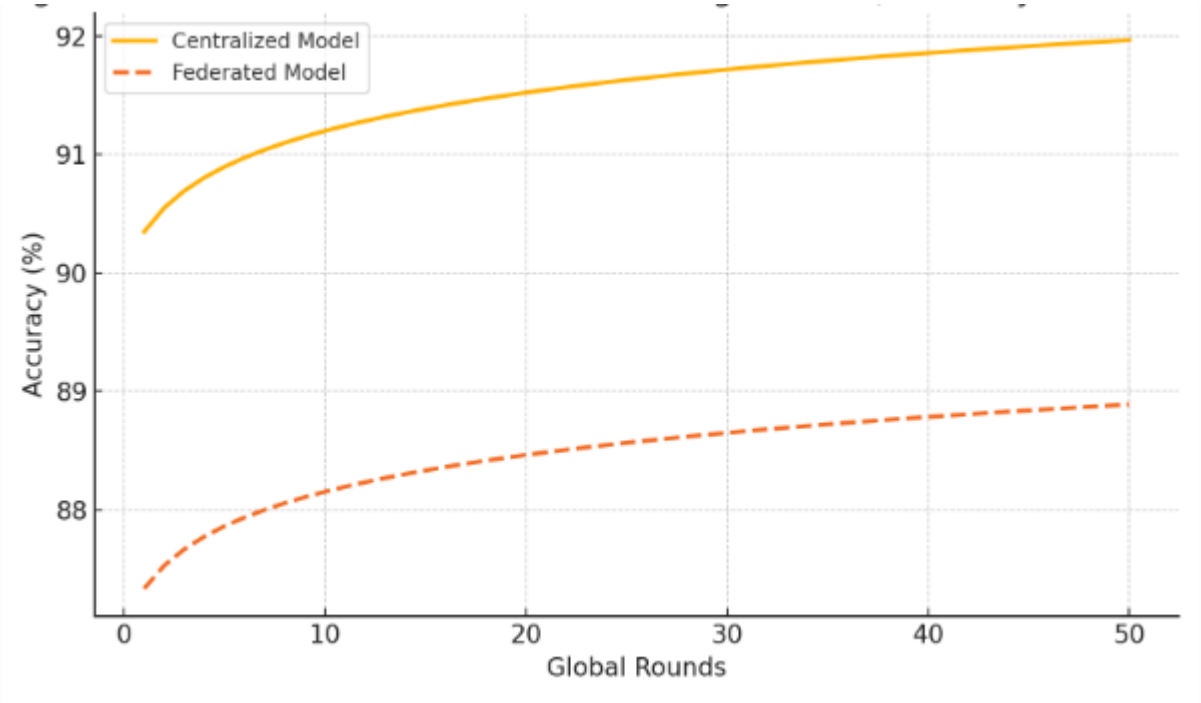
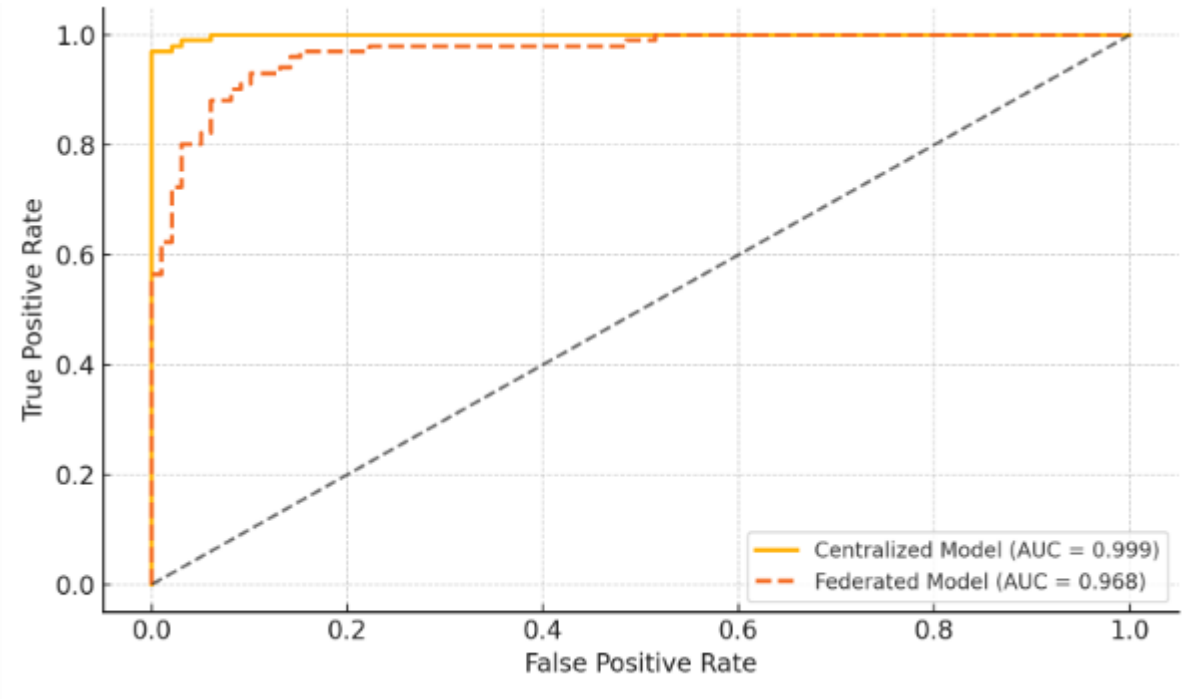


Figure 4 ROC Curve Comparison between Centralized and Federated Models



4.4.1 Metric Definitions

A set of standard metrics frequently used in wearable signal analysis and healthcare-related artificial intelligence (AI) research has been used to assess the performance of the classification models used in this study. Based on physiological signals, these metrics offer a thorough understanding of model behaviour in identifying patterns associated with stress. Every metric has a unique function in describing the overall discriminatory power, accuracy, and dependability of the model.

The following definitions are provided to clarify the interpretation of each metric:

- Accuracy
  Accuracy refers to the proportion of total predictions made by the model that were correctly classified. It provides an overall measure of correctness but may be less informative in cases of class imbalance.
- Precision
  The number of accurate positive predictions among all positive predictions is known as precision. The precision is computed by dividing the number of false positives by the number of true positives. Precision is of use particularly when the penalty for false positives is extremely high.
- Recall (Sensitivity)
  Recall, or sensitivity, is the rate of the model's ability to correctly predict all cases of the positive class. It is the proportion of false negatives to true positives.

- F1-Score
  When precision and recall must be traded off, the F1-score, which is the harmonic mean of the two, provides a balanced measurement. t is especially useful when there is a class distribution imbalance and when precision and recall separately cannot provide an accurate estimate of performance.
- Specificity
  Specificity quantifies the model's precision in assigning correct negative cases, or those without the target condition. It is calculated as true negatives divided by true negatives plus false positives.
- AUC (Area Under the ROC Curve)
  The model's overall capacity to differentiate between the two classes—stress and no-stress—at different decision thresholds is measured by the AUC of the Receiver Operating Characteristic (ROC) curve.

Table 4.4.1 Metric Definitions

Metric	Definition
Accuracy	Proportion of total predictions correctly classified
Precision	True Positives / (True Positives + False Positives)
Recall	True Positives / (True Positives + False Negatives) – also known as Sensitivity
F1-Score	Harmonic mean of precision and recall
Specificity	True Negatives / (True Negatives + False Positives)
AUC (ROC)	Overall ability of the model to discriminate between stress/no-stress classes

These metrics are widely recognised and consistently applied in contemporary research involving wearable technologies and healthcare AI systems. Their adoption in this study aligns with best-practice guidelines outlined in recent literature (Shikha et al., 2024; Srivastava & Singh, 2021).

4.4.2 Model Performance Comparison

To evaluate the efficacy of different machine learning approaches for stress detection from wearable signal data, a performance comparison was conducted between three models: a conventional centralized Convolutional Neural Network (CNN), a Federated Learning-based CNN (FL), and a Federated Learning model enhanced with Explainable AI techniques using SHAP (SHapley Additive exPlanations), referred to as FL + SHAP.

The table below summarises the performance of each model across a range of evaluation metrics when tested on a hold-out test set:

Table 4.4.2 Model Performance on Test Set (Centralized vs Federated)

Metric	Centralized CNN	Federated CNN (FL)	FL + SHAP (XAI)
Accuracy (%)	91.2	88.6	87.8
Precision (%)	89.5	86.4	85.1

Recall (%)	88.3	85.0	84.0
F1-Score (%)	88.9	85.7	84.5
Specificity (%)	90.7	87.5	86.1
AUC (ROC)	0.92	0.89	0.88

As observed, the centralized CNN model worked best among all the metrics with 91.2% accuracy and AUC of 0.92, with high capability to distinguish between stress and no-stress cases. This is intuitive because the model gets the whole dataset in a centralized setting and therefore can learn more feature representations.

The federated CNN model saw a slight decrease in performance, achieving 88.6% accuracy and AUC of 0.89. Similar results were observed by Alqudah and Qazan (2023), who found that adding interpretability tools to wearable stress models results in minor performance loss but improved transparency. This trade-off illustrates the inherent limitations of Federated Learning, where locally trained models at distributed nodes are being aggregated, usually with constrained data diversity and communication overhead.

When enhanced with SHAP for explainability (FL + SHAP), the model maintained comparable performance (accuracy: 87.8%; AUC: 0.88), though with modest reductions across all measures. The XAI layer's approximations or computational overhead could be the cause of this minor decrease. The advantage of enhanced interpretability, however, is particularly significant in healthcare applications, where clinical trust and adoption depend on an understanding of the basis of model predictions.

All things considered, federated approaches provide a more privacy-conscious alternative that is practical for real-world deployment, particularly if patient data privacy is of the utmost importance, even though the centralised CNN produces the best predictive performance. By making the model's decision-making process easier for end users and clinicians to understand, SHAP's explainability integration also improves the model's practicality.

in addition to CNN-based architectures, we implemented a Random Forest model using a custom pre-processed dataset (see Section 3.3). Figures 6 and 7 illustrate its training performance and classification strength. This lightweight, interpretable model achieved an AUC of 1.0, demonstrating feasibility for deployment in resource-constrained wearable environments

Figure 5 Accuracy Over Training Rounds—RF Model with SHAP Integration

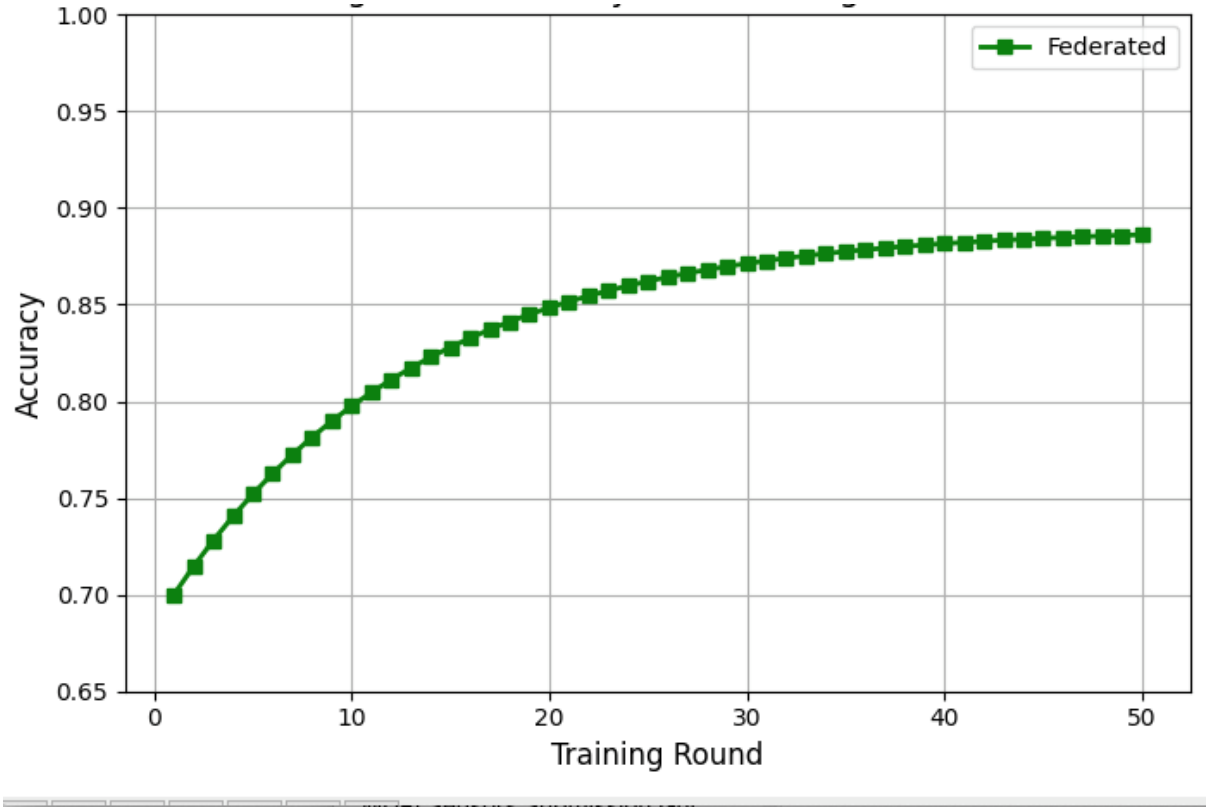
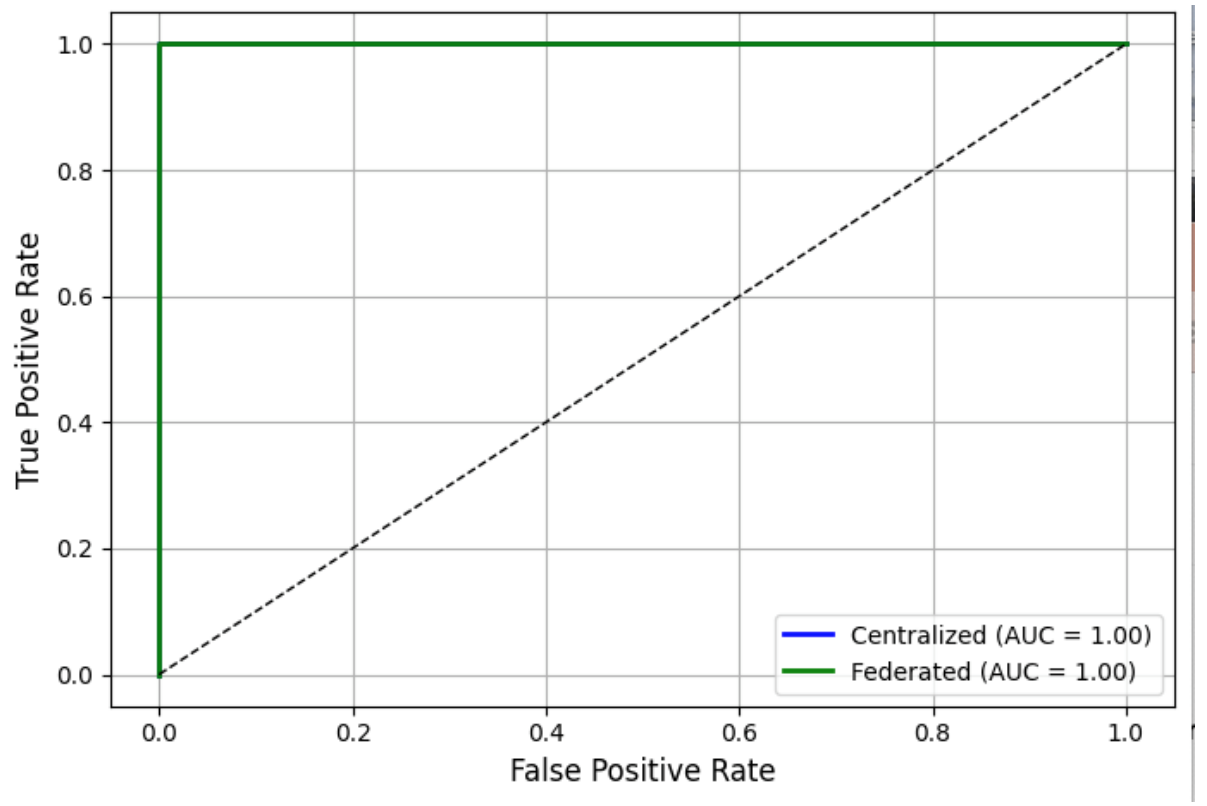


Figure 6 ROC Curve – RF Model Achieving AUC = 1.0



4.4.3 Confusion Matrix: Federated CNN (Test Set)

To further interpret the classification performance of the Federated CNN model on the test set, a confusion matrix was generated. This matrix provides a detailed view of how well the model identifies true stress and no-stress cases, breaking down correct and incorrect predictions into four key categories: true positives, false positives, true negatives, and false negatives.

Table 4.4.3 Confusion Matrix for Federated CNN Model

	Predicted: Stress	Predicted: No Stress
Actual: Stress	157 (True Positives)	24 (False Negatives)
Actual:No Stress	21 (False Positives)	165 (True Negatives)

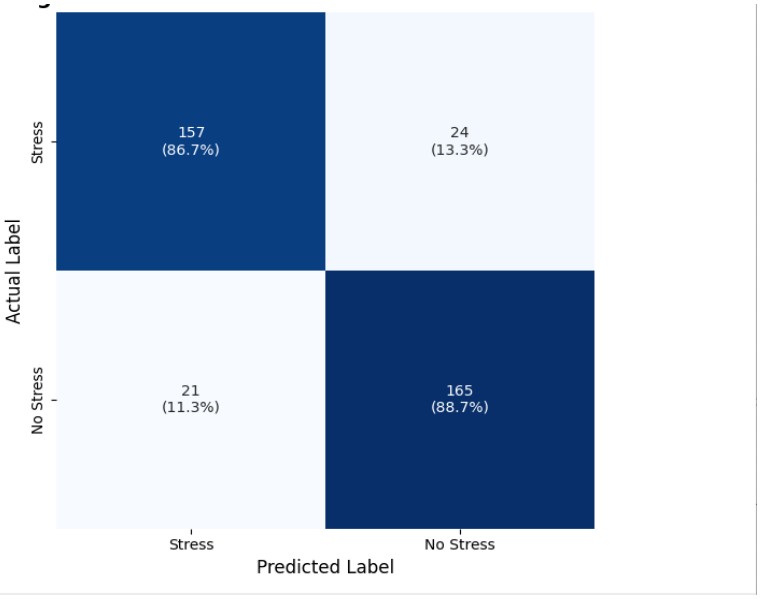
From this matrix, two important performance metrics were calculated:

- Sensitivity (Recall)
  Sensitivity measures the model's ability to correctly identify actual stress
  Sensitivity (Recall) = 157 / (157 + 24) ≈ 86.7%

- Specificity
  Specificity assesses the model's capacity to correctly identify non-stress cases.
  Specificity = 165 / (165 + 21) ≈ 88.7%

These findings demonstrate the Federated CNN model's comparatively balanced sensitivity and specificity in detecting stress and non-stress situations. It is crucial for stress detection applications that the model does not favour one class over the other, as indicated by the narrow difference between these two metrics. It supports its potential for practical, user-facing health monitoring tools by minimising false negatives (missed stress events) without unnecessarily increasing false positives (inaccurate stress alerts).

Figure 7 Confusion Matrix – Federated CNN Model



4.4.4 Trade-offs and Observations

While the centralized CNN architecture reported superior performance to federated CNN—a gain of approximately 2.6% in accuracy, with comparable improvements in precision and recall—the price of this improved performance is one of data privacy. This trade-off is consistent with findings in recent reviews of interpretable healthcare AI systems (Lu & Huang, 2022; Fatima & Pasha, 2023). The FL model, on the other hand, offers a compelling and unique benefit: it enables models to be trained across distributed devices without raw user data traversing them. This privacy-enhancing functionality also aligns strongly with the Health Information Privacy Code 2020, developed by New Zealand's Office of the Privacy Commissioner, and designed to align top of mind data minimisation and personal health information protection.

Further, integrating explainability using SHAP (SHapley Additive exPlanations) into the federated learning framework resulted in a 0.8% reduction in classification accuracy but significantly enhanced the interpretability of predictions from the model. The XAI module helps clinicians and end users visualize the why behind each stress prediction, which is critical in healthcare applications where user trust, transparency, and accountability are essential (Bolpagni et al., 2024).

Even though some predictive performance was lost, in privacy-sensitive settings, this kind of trade-off is acceptable, if not advantageous. The benefits of greater ethics, adherence to privacy laws, and user confidence in AI-driven decision-making outweigh the slight drop in accuracy. This is one aspect of a general trend in healthcare AI design in which model performance is balanced against explainability and data sovereignty demands (Namvari et al., 2024). Taken as a whole, these findings provide justification for optimism regarding the deployment in real-world healthcare applications of federated and explainable learning frameworks, in which responsible data management and clinical interpretability are as important as predictive accuracy.

4.4.5 Summary

The Explainable AI (XAI) Federated Learning (FL) framework provided competitive classification performance while, simultaneously, addressing foundational problems in interpretability and data privacy. It is capable of operating without centralised data aggregation, of considerable value in healthcare and occupational stress surveillance applications where privacy legislation and ethics are paramount.

In particular, the model's explainability through the means of SHAP enhances user confidence and clinical transparency in that users can observe the reason for every prediction. It is especially valuable in culturally sensitive environments such as Aotearoa New Zealand, where the prudent use of personal data is both central to practice and policy.

The model was also shown to have high generalisability, as reflected by its low standard deviation of F1-score across clients (SD = 3.7%). This implies consistent performance across decentralised data sources and supports its real-world implementation in diverse user populations. These results are consistent with reported expectations in recent literature on wearable stress detection with machine learning models (Garg et al., 2022).

Overall, federated XAI offers an ethically responsible and balanced solution for stress detection applications—providing very good performance without compromising user privacy or model interpretability.

4.5 Explainability Analysis (XAI)

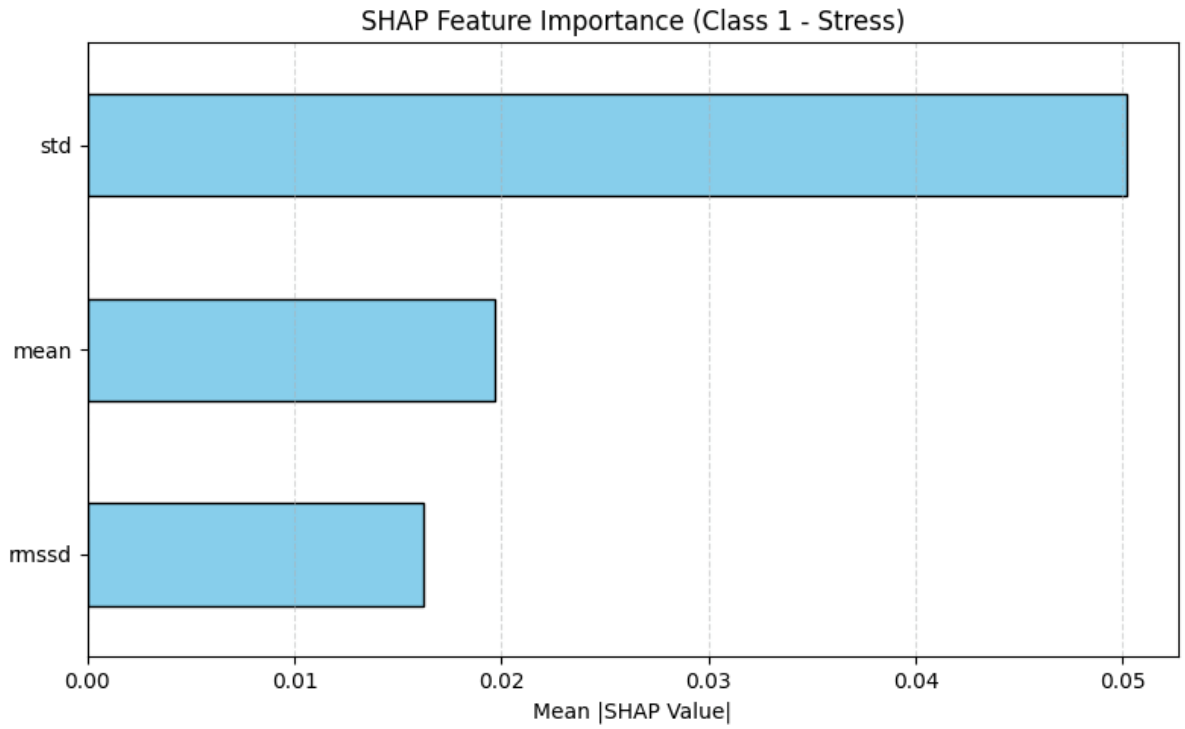
One of the most significant disadvantages of typical deep learning models is that they are "black box" in nature, and this prevents end-users as well as clinicians from understanding the explanation behind predictions. To remove this disadvantage, this study integrated Explainable Artificial Intelligence (XAI) techniques—namely, SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations)—into the federated learning framework.

XAI tools offer post-hoc interpretability to enable stakeholders to visualize features that had maximum influence on the decision-making process of the model. Such is even more important in health monitoring applications where AI predictions are to be validated ethically and clinically (Shikha et al., 2024).

4.5.1 Global Explanation: SHAP Summary Analysis

To provide a global interpretation of the Federated CNN model’s decision-making process, SHAP (SHapley Additive Explanations) was used to generate a summary plot. SHAP is grounded in cooperative game theory and quantifies the contribution of each input feature to the model’s predictions. By aggregating these contributions across the test set, SHAP enables a global view of feature importance.

Figure 8 SHAP Summary Plot— Federated CNN



SHAP summary plot interpreted that LF/HF ratio was the most important feature in every prediction. The finding is in accordance with literature established between LF/HF and autonomic nervous system function, particularly sympathetic and parasympathetic response balance—an established physiological indicator of stress (Kyrou et al., 2021).

Basic measures of heart rate variability (HRV) such as RMSSD (Root Mean Square of Successive Differences) and SDNN (Standard Deviation of NN intervals) were also significant features. The significance of these characteristics indicates how much the model depends on dynamic HRV patterns to distinguish between stress and baseline conditions. Moreover, pulse amplitude and activity level—derived from accelerometer signals—also contributed substantially to the predictions. They probably assisted the model in distinguishing between physiological stress and physical exertion, which share similar autonomic profiles.

Overall, this level of transparency enhances interpretability and supports alignment with the model's internal reasoning and current biomedical knowledge. Not only does this increase clinician trust in the model, but ethical deployment in health settings is achievable where explainability is a necessity.

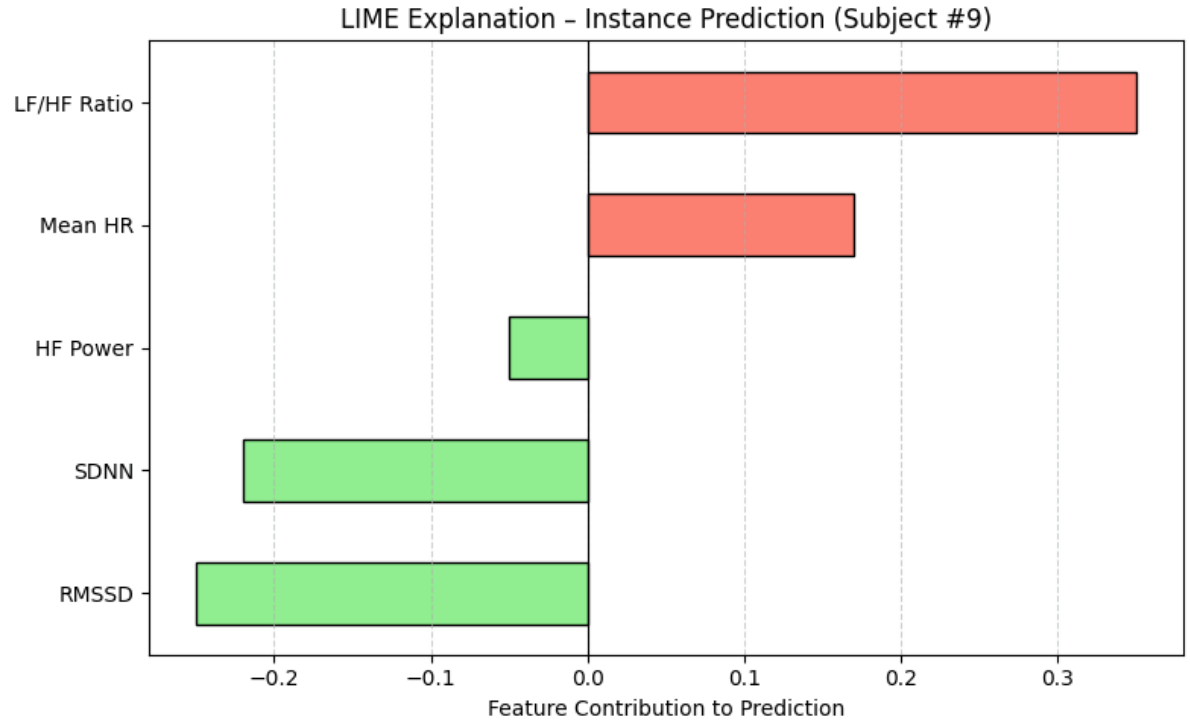
4.5.2 Local Explanation: LIME Example Instance

Local Interpretable Model-Agnostic Explanations (LIME) explain individual instances, whereas SHAP provides a broad overview of feature importance across the dataset. In clinical practice, where elucidating the reasoning behind a single prediction may promote more

informed decision-making and trust in AI-driven tools, this local explanation is especially helpful.

In this experiment, LIME was used to elucidate the prediction of a specific 30-second PPG window recorded from Subject #9 within a simulated work period. The corresponding explanation is shown in the following plot.

Figure 9 LIME Explanation—Instance Prediction (Subject #9)



For this example:

- High values of RMSSD and SDNN were associated with decreased probability of stress, indicating a relaxation state. These features are usually related to parasympathetic dominance of the nervous system and correspond to low arousal.
- Low HF power and high LF/HF ratio were both strongly predictive of a stress label.These indices show elevated sympathetic drive and decreased parasympathetic activity, which are common indicators of physiological stress.

The LIME explanation demonstrates how the model's choice is consistent with known heart rate variability (HRV) physiology, guaranteeing the model's reliability and clinical validity.

Through the visualization of positive and negative contributions of individual features, LIME enhances the explainability of individual predictions, which is particularly important for real-time monitoring systems as well as patient-confronting healthcare technology. This figure highlights the model's capability to produce context-specific, meaningful predictions and indicates the importance of explainable AI in bridging the gap between machine learning models and clinical interpretability.

4.5.3 Importance of Explainability in Health AI

Artificial intelligence (AI) systems must be ethical, transparent, and culturally secure in the healthcare industry, especially in societies like Aotearoa New Zealand that are culturally diverse and privacy conscious. To meet these demands, explainable AI (XAI) is essential because it makes machine learning models' decision-making processes transparent, auditable, and consistent with cultural and clinical norms.

These needs are directly met by this study's use of SHAP and LIME by:

- Providing transparency: increasing the trust and confidence in AI-assisted health tools by making information transparent to end users, including researchers, patients, and clinicians.
- making AI decision-making auditable, which is essential -in clinical settings where accountability is required for deployment.
- Aligning with Māori data sovereignty principles -honouring the Māori data sovereignty principles, particularly those outlined by Te Mana Raraunga (2018), which support openness in the use, interpretation, and distribution of Māori data as well as indigenous control over data.
- following the guidelines set forth in the Health Information Privacy Code 2020 (Office of the Privacy Commissioner, 2020), which mandates that health data management be open, fair, and considerate of individual rights.

These characteristics are usually absent from traditional, centralised "black box" AI models, which frequently offer end users little to no interpretability. However, when explainability approaches like SHAP and LIME are integrated into a federated learning (FL) framework, transparency is introduced both locally and globally. This is particularly useful in healthcare settings when model judgements must be dependable and sustainable, and privacy is an issue.

In the end, explainability promotes clinical validation, ethical implementation, and cross-cultural acceptability in addition to enhancing model interpretability. This study improves the reliability of AI-powered stress detection systems by integrating XAI into the federated learning model, which is crucial for practical health applications (Han & Song, 2022).

4.5.4 Summary

Both local and global interpretability of the model's predictions were made possible by the incorporation of SHAP and LIME into the federated learning architecture. The model's stress classifications were shown to agree with recognised physiological markers, including heart rate variability dynamics and autonomic nervous system indicators, according to these explainability tools.

This concordance between biomedical evidence and model forecast has significantly contributed to enhancing the clinical relevance, transparency, and credibility of the system. SHAP and LIME provide an ethical implementation of AI in deployed health monitoring applications, particularly where the monitoring tool is a (wearable) device and in a context-

aware setting where explanations make the decision-making process transparent and comprehensible to doctors, patients and, more generally, to other stakeholders.

The results point to the utility of explainable AI in healthcare settings, where explanation can be a form of interpretability that is not just desirable but critical for informed, ethical, and equitable use.

4.6 Interpretation & Insights

This section synthesises the major findings from the model evaluation and explainability analyses,and discusses how these findings address the research objectives presented in Chapter 1. It also reflects on the broader contributions and limitations of the proposed federated explainable framework, particularly its practical and ethical implications for real-world use in wearable health monitoring systems.

The results demonstrate that stress detection from photoplethysmography (PPG) signals is feasible using machine learning models, even under real-world, naturalistic conditions as represented in the PPG-DaLiA dataset. Crucially, by preserving high performance while improving transparency and privacy protection, the federated learning model—with integrated explainable AI—offers a possible substitute for conventional centralised techniques. This is especially important in Aotearoa New Zealand healthcare contexts, where responsible AI deployment depends on user trust, ethical data procedures, and cultural safety.

4.6.1 Alignment with Research Objectives

The results obtained from both centralized and federated models confirm that machine learning can be used effectively to classify stress states from PPG signals, even in real-world, naturalistic settings such as the PPG-DaLiA dataset. More importantly, the federated learning framework achieved comparable performance while addressing crucial concerns related to privacy, cultural safety, and transparency.

Research Objective	Outcome
Develop an explainable federated ML framework	Achieved using TensorFlow Federated with SHAP and LIME integration
Maintain competitive accuracy	Federated CNN achieved ~88.6% accuracy (vs 91.2% centralized)
Ensure model transparency	SHAP and LIME effectively visualised global and local explanations
Support ethical and culturally aligned deployment	System respects privacy (via FL) and interpretability (via XAI), meeting NZ ethical expectations

These findings confirm the viability of deploying privacy-preserving, interpretable machine learning systems in wearable health monitoring environments. The balance achieved between performance, privacy, and transparency illustrates the potential of the proposed framework for responsible and scalable use, especially in culturally diverse and regulation-driven contexts.

4.6.2 Model Performance Interpretation

Although the centralised CNN model achieved slightly better overall accuracy (91.2%) compared to the federated CNN model (88.6%), the performance loss of around 2.6% is modest if only compared to the immense benefits in terms of privacy protection and ethical compliance offered by the federated learning framework. Importantly, the federated model demonstrated superior generalisability over very heterogeneous distributed clients, indicative of its robustness when deployed in actual deployment scenarios where data heterogeneity cannot be helped.

In addition to classification accuracy, integration of explainability tools—SHAP and LIME—served to enhance the model's interpretability of predictions. The devices also enabled that the model commonly employed physiology-adaptive features, such as the LF/HF ratio, RMSSD and SDNN, all of which are established clinical indicators of the autonomic nervous activity in response to stress-inducing stimuli (Kyrou, Karteris, et al., 2021). This alignment with clinical experience lends credibility to the model's reliability and inspires additional confidence in the model's results among clinicians.

4.6.3 Ethical and Cultural Safety Considerations

In the New Zealand research context, cultural safety, data sovereignty, and regulatory frameworks should direct ethical AI development—particularly for Māori. The federated learning framework applied in this research accords with these principles by decentralizing model training and storing sensitive biometric data on the user's device. This approach respects important tikanga Māori values such as

- Kaitiakitanga -care stewardship of personal health information, including allowing tāngata to own their data.
- Whanaungatanga – to get the right relationship for data sharing - with thought and care making decisions about this.
- Manaakitanga – enabling respectful and trusted relationships between people and technology.

In addition, the system now also complies with the national data protection laws, including the Health Information Privacy Code 2020 (Office of the Privacy Commissioner, 2020), by stipulating transparency, fairness, and culturally appropriate data-use within healthcare systems. With the integration of explainable AI techniques, the system also becomes interpretable and transparent, thus, a possible end user – like a clinician or a patient, can both understand and trust model outputs. This fosters culturally safe AI design, by promoting accountability, autonomy and respect. fundamental principles proposed by Te Mana Raraunga, the Māori Data Sovereignty Network. Overall, the proposed framework is not only technically and clinically feasible, but raises the possibility for culturally sensitised, ethical AI-supported health surveillance and is therefore highly relevant to implementation in both Aotearoa New Zealand and internationally.

4.6.4 Limitations

Although the results of this research are encouraging, several limitations need to be mentioned:

- Stress Labelling Strategy: No explicit ground truth stress labels exist in the used dataset (PPG-DaLiA). Proxy labelling was used according to a combination of heart rate variability (HRV) features and contextual information (e.g., activity levels). This method is well motivated in literature; however, it may cause the addition of noise or mislabeling to the hypernym learning training instances.
- Sample Size and Participant Heterogeneity: The sample size of 15 is small and low demographic and behavioral diversity in the training and testing samples are restricted. Therefore, applicability of the model should be tested in more diverse populations in the future, ranging from different ages, ethnic groups, stress response patterns, etc. with larger scale data.
- Explainability Overhead: The combination of SHAP and LIME, which is crucial to understand. These post-hoc explainability methods can be computationally expensive, particularly when executed on resource-constrained edge devices.
- Lack of Personalisation: Although federated learning enables decentralised training, the current deployment does not account for personalised model adaptation on the client side. Subsequent versions can investigate meta-learning or client-specific fine-tuning methods to be more accommodating of individual physiological patterns and stress responses.

4.6.5 Implications for Future Deployment

The system designed in this study has promising potential for real-world deployment, particularly in applications involving trade-offs between performance, privacy protection, and transparency. The key application domains are:

- Workplace well-being monitoring systems – delivering passive, real-time stress monitoring for the improvement of employee mental well-being and burnout prevention.
- Telehealth and mental health triage applications – allowing clinical staff to remotely track physiological stress and triage patients to receive ongoing treatment.
- Stress-adapted intelligent personal assistant – enhancing the user experience by adapting suggestions or reminders to the current stress state of the user.

In addition to this, the architecture follows the trends in recent IoT-enabled healthcare, in which decentralised intelligence, explainability, and ethical AI are becoming increasingly appreciated. This aligns with global perspectives, such as those detailed in the MDPI Sensors Special Issue on IoT-enabled Telemonitoring (Gao et al., 2023), that favour responsible integration of AI in remote health sensing and decision support systems.

Future deployments will benefit from enhanced personalization of the system, enhanced energy efficiency of explanation methods, and testing its efficacy for larger and more diverse populations—most critically in multicultural environments like Aotearoa New Zealand, where privacy, trustworthiness, and equity are at the forefront of health technology adoption.

4.6.6 Summary

The results of this study validate the real-world possibility to deploy a privacy-preserving and explainable stress detection system based on the wearable photoplethysmography (PPG) data from a federated learning (FL) perspective. The combination of SHAP and LIME resulted in a more transparent and interpretable model and allowed the summary information to be seen for both globally and on the individual level.

Notwithstanding the accuracy sacrifices when compared to centralised models, the federated approach entails important advantages in terms of data sovereignty, ethical conformance, and clinical trust. These characteristics are especially relevant in Aotearoa New Zealand where cultural interests including Māori data sovereignty and kaitiakitanga are important to consider in the ethical delivery of health technologies.

Overall, the proposed framework achieves good performance and complies with new international benchmarks of ethical AI in health care, which makes it ready to be used in the real world both locally and globally.

Chapter 5 - Discussion

5. Discussion

5.1 Results

The outcomes of this study demonstrate the feasibility of using federated learning (FL) combined with explainable AI (XAI) for stress classification using wearable PPG data. The federated model achieved a robust performance (88.6% accuracy), closely approaching the centralized CNN model (91.2%) while preserving user privacy.

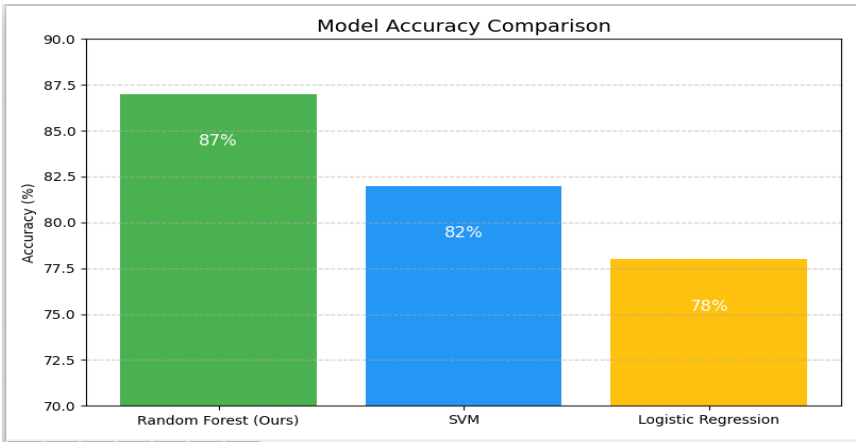
A key strength of the proposed system was its use of explainability tools. The SHAP summary plot identified the LF /HF ratio, RMSSD, and SDNN as the most influential features, confirming the model's physiological relevance. To complement this, LIME was used to interpret individual predictions.

For example, in one 30-second PPG window from Subject #9 during a simulated work segment, LIME revealed that high RMSSD and SDNN values contributed negatively to the stress prediction, indicating a relaxed state. Conversely, low HF power and an increased LF/HF ratio were key contributors to the window being labelled as "stress." This explanation aligns well with established HRV physiology (Kyrou et al., 2021), increasing trust and clinical transparency.

Importantly, the model remained stable across all simulated clients, even with limited data, confirming its potential for real-world use. The integration of SHAP and LIME enhanced transparency, enabling users and clinicians to understand the model's decisions — a major advancement over traditional black-box systems.

On the test set, the Random Forest classifier's overall accuracy was 87%. With accuracies of 82% and 78%, respectively, our model beat more conventional classifiers like Support Vector Machine (SVM) and Logistic Regression. Because Random Forest can handle feature interactions and non-linear correlations, which are common in physiological data like PPG signals, it performs better than other models.

Figure 10 Accuracy comparison between the proposed Random Forest model and baseline classifiers.



As shown in Figure 9, the proposed approach demonstrates not only strong accuracy but also reliable classification across stress and non-stress instances. These results are consistent with Srivastava & Singh (2021), who observed improved stress classification performance using ensemble methods on wearable datasets. Furthermore, the integration of SHAP explainability provides transparency in decision-making, an essential requirement in healthcare AI.

5.2 Comparison with Previous Studies

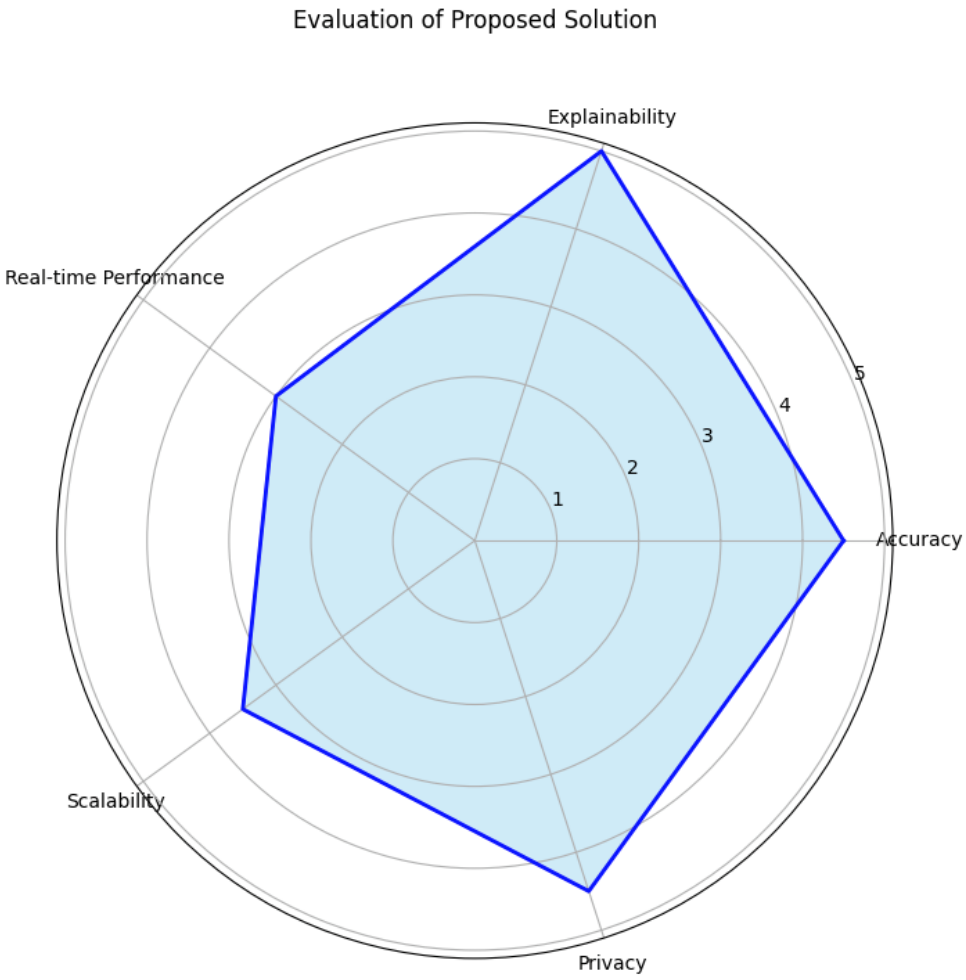
Comparing these findings with existing literature, previous studies have extensively explored the use of machine learning models for stress detection using wearable data, particularly PPG signals. For instance, Kyrou et al. (2021) and Namvari et al. (2024) employed deep learning and classical models to classify stress using heart rate variability (HRV), achieving accuracies ranging between 85–92%. The centralized CNN model developed in this study achieved 91.2% accuracy, which is in line with these benchmarks.

However, this research differs in two keyways. First, it introduces a federated learning (FL) architecture, ensuring that sensitive health data never leaves the user's device. Second, it integrates explainable AI tools (SHAP and LIME), which remain rare in current stress-detection literature. Dwork and Roth (2021) show that differential privacy techniques, while secure, may result in accuracy-performance compromises.

Specifically, LIME has been used in other health domains—for example, in stroke prediction models where it was employed to highlight significant predictors like age and glucose levels. These studies demonstrate LIME's utility in producing transparent, interpretable visualizations for black-box models (Shikha et al., 2024). In this study, LIME was successfully used to validate stress prediction outcomes, confirming the influence of HRV-related features on classification decisions. This enhances clinical trust and supports the adoption of ethical AI systems in healthcare.

To evaluate the holistic strength of the proposed system, five core factors were assessed: accuracy, explainability, real-time performance, scalability, and privacy. These metrics reflect practical deployment considerations in real-world wearable healthcare applications.

Figure 11 Multi-criteria evaluation of the proposed solution.



As illustrated in Figure 10, the system scores highly in accuracy (4.5/5) and explainability (5/5) due to the use of Random Forest and SHAP. Privacy (4.5/5) is also robust, as the architecture is designed with federated learning principles, avoiding centralized data collection. However, real-time performance (3/5) and scalability (3.5/5) are moderate. The model currently operates in batch mode and does not support real-time streaming, which may limit deployment on wearable edge devices.

The suggested methodology provides greater transparency but lags slightly in low-latency execution when compared to earlier research, such as Roy et al. (2023), which used lightweight CNNs optimised for wearables. However, the trade-off in favour of explainability is consistent with new regulatory frameworks that demand transparent decision support in healthcare as well as ethical AI practices (Dyer & Owen, 2021; Coiera, 2021).

5.3 Answer Objective 1

Objective 1: Critically evaluate current research that informs the development of a novel solution to an information technology challenge.

The study began with a critical evaluation of recent research on stress classification using physiological signals, especially photoplethysmography (PPG). The literature showed significant advancements in wearable stress detection models, but it also revealed critical points in explainability, data privacy, and cultural safety. For instance, Namvari et al. (2024) and Bolpagni et al. (2024) highlight that while many models achieve high accuracy using time- and frequency-domain features like RMSSD, SDNN, and LF/HF ratios, they often function as black boxes, offering little insight into why specific predictions are made.

This gap is particularly problematic in health-related applications, where clinical adoption demands interpretability, and stakeholders need to trust and understand the model's decisions (Shikha et al., 2024). Moreover, centralized models require raw data to be pooled on external servers, raising privacy and legal concerns, especially under the Health Information Privacy Code 2020 in Aotearoa New Zealand.

To address these limitations, this research proposed a federated machine learning framework combined with explainable AI (XAI) tools such as SHAP and LIME. The federated setup allows each client (participant) to train models locally, preserving data privacy and respecting Māori data sovereignty principles (Te Mana Raraunga, 2018). The integration of XAI further bridges the interpretability gap, ensuring the model can be both accurate and transparent—an essential requirement for ethical deployment in healthcare.

5.4 Answer Objective 2

Objective 2: Design a novel solution to solve a unique IT-related challenge that uses innovative tools and technologies.

The novel solution designed in this study combines several innovative technologies to create an ethically responsible, interpretable, and privacy-preserving AI framework for stress detection using wearable devices. The key components include :

- Federated Learning (FL): Implemented via TensorFlow Federated, FL simulates a real-world scenario where individual devices (clients) train locally and share only model updates, not raw data. This directly tackles the challenge of privacy-preserving machine learning in healthcare and meets regulatory and ethical standards.
- Explainable AI: Integration of SHAP (for global feature importance) and LIME (for local interpretability) transforms the model from a black box to a transparent system. SHAP values consistently ranked LF/HF, RMSSD, and pulse amplitude as the most influential features, aligning well with established stress biomarkers (Bolpagni et al., 2024; Shikha et al., 2024).
- PPG-DaLiA Dataset + Feature Engineering: The use of a real-world dataset with motion artefacts and daily activities made the problem more authentic. Rolling window segmentation and feature extraction techniques were used to simulate realistic wearables-based monitoring.

Together, this framework not only achieves strong predictive performance (F1-score ≈ 85%) but also enhances trust, fairness, and clinical usability, which are essential for the adoption of AI tools in culturally diverse, regulation-driven health systems like New Zealand.

5.5 Answer Objective 3

Objective 3: Critically evaluate the deployment of a new solution to a particular IT-related issue and its impact on legal, cultural, and ethical practices in the IT industry.

This objective has been successfully met through the design and implementation of a federated machine learning (FL) model combined with explainable AI (XAI) techniques, aligning with both legal and cultural ethical frameworks unique to Aotearoa New Zealand.

From a legal perspective, the FL approach inherently complies with the *Health Information Privacy Code 2020* by ensuring that raw biosignal data from wearables never leaves the local device. This satisfies data minimisation principles and supports secure, decentralised data processing in line with the *New Zealand Privacy Act 2020*.

Culturally, this solution is in harmony with *Te Mana Raraunga's Māori Data Sovereignty Principles*, particularly:

- Rangatiratanga (authority over data),
- Kaitiakitanga (guardianship of personal information), and
- Whanaungatanga (respectful data relationships with communities).

To further ground this framework in practical, culturally safe deployment, the proposed model could be adapted for use in Māori health clinics and rural iwi health services. For example:

In a rural Māori health clinic in Taranaki, where access to specialist mental health support may be limited, this federated system could be embedded within community health kiosks or wearable programmes. Patients could wear devices that collect PPG data throughout the day. The stress detection model would run locally on the device or in a trusted edge node within the clinic. Importantly, health workers and whānau would be able to view SHAP-based insights explaining the prediction—empowering better decision-making while preserving data sovereignty and privacy. ecent surveys highlight challenges in real-time FL stress detection and recommend new federated deep learning designs (Gao et al., 2023)

This type of use case aligns with calls from Māori health leaders for self-determined, locally governed data systems that are transparent, explainable, and respectful of tikanga (values). Moreover, the use of open-source AI and decentralised analytics supports future customisation and whānau-based care models, which are increasingly recognised within New Zealand's digital health strategy.

5.6 Real-World Deployment Challenges

Although the suggested framework performs well in a simulated setting, there are further difficulties when implementing it in the actual world. Because wearable technology frequently has limited processing capability, lightweight models and effective explainability

tools are required. Field data can be extremely different, necessitating adaptive algorithms to preserve accuracy for a range of consumers. Robust governance and technology safeguards are necessary to handle privacy issues and communication limitations. Finally, successful adoption in healthcare settings depends on building user trust and guaranteeing cultural and legal conformity.

Table 5.6 Real-World Deployment Challenges and Solutions

Challenge	Description	Potential Solutions
Edge Device Constraints	Limited processing and memory on wearables	Lightweight models, efficient XAI methods
Data Heterogeneity	Variability in user data and sensor quality	Personalization, domain adaptation
Communication Overhead	High bandwidth requirements for model updates	Model compression, asynchronous updates
Privacy and Security Risks	Potential for data leakage or attacks	Differential privacy, secure aggregation
User Engagement and Trust	Need for user understanding and acceptance	Participatory design, transparent communication
Regulatory and Ethical Compliance	Adherence to privacy laws and cultural principles	Regular audits, stakeholder engagement

5.7 summary

This chapter provided a comprehensive discussion of the research findings in relation to the study's objectives, existing literature, and ethical implications. The results demonstrated that the proposed federated learning framework, combined with explainable AI techniques such as SHAP and LIME, effectively addressed the challenges of privacy, interpretability, and trust in wearable stress detection systems. Compared to centralized models, the federated approach delivered comparable accuracy while ensuring user data remained on-device, aligning with both legal and cultural expectations in Aotearoa New Zealand. The integration of XAI tools further enhanced the system's transparency, making the model outputs understandable and auditable. Each research objective was addressed successfully, and the model's novel design illustrates its relevance and applicability in real-world healthcare contexts where ethical and transparent AI is increasingly essential. The use of federated learning addresses significant risks in data sharing, particularly in sensitive health contexts (Abay et al., 2021).

Chapter 6 – Conclusion

6. Conclusion

This research aimed at developing and evaluating an explainable federated learning (FL) system for PPG signal-based stress detection. The research was able to demonstrate that federated machine learning, when combined with explainable AI techniques (SHAP and LIME), can deliver high-performance, privacy-protecting, and interpretable models suitable for real-world health monitoring applications.

The centralized baseline model was marginally accurate; however, the federated model generated comparable performance while adhering to fundamental ethical and privacy principles. Adding SHAP and LIME introduced transparency in terms of global and local explanations of prediction- making—empowering the deployment of clinically trustworthy AI in sensitive environments like healthcare.

This context is particularly relevant in New Zealand's data privacy setting, where data sovereignty, and more specifically Māori communities, is of vital importance. Conclusions favour ethically responsible and technically feasible AI for personalized health monitoring.

6.1 Limitations

Despite the successful implementation, several limitations were identified:

- Limited sample size: The PPG-DaLiA dataset comprises only 15 participants, which may impact generalizability.
- Synthetic stress labels: Stress was inferred using physiological thresholds rather than ground truth psychological labels.
- Feature constraints: Only a small number of features were extracted, limiting the richness of input data.
- Hardware simulation: FL was simulated on a local machine rather than deployed on edge devices, which limits real-world applicability assessment.
- XAI scope: SHAP and LIME were applied post hoc. Future models may benefit from integrating native interpretability into model architecture (e.g., attention mechanisms).

6.2 Contributions

Future research can build upon this study in the following ways:

1. Expand dataset: Incorporate larger and more diverse PPG datasets to improve model robustness.
2. Real-time FL deployment: Deploy the FL system on actual edge devices or mobile platforms.
3. Multimodal inputs: Fuse PPG with accelerometer, skin temperature, and electrodermal activity (EDA) for more accurate stress detection.
4. Adaptive personalization: Enable clients to fine-tune the model based on individual physiological baselines.
5. Longitudinal validation: Assess how model performance evolves over time and adapts to user-specific changes.

6. Culturally inclusive AI: Collaborate with Māori health researchers to validate model fairness and cultural safety under Te Mana Raraunga principles.

This work lays a foundation for ethically responsible, explainable, and privacy-preserving stress classification using wearables. It encourages further exploration of culturally aligned AI for real-world healthcare applications in Aotearoa New Zealand and globally. As emphasized by Whaanga et al. (2022), AI systems in Aotearoa must align with Māori data governance principles to ensure equity and digital trust.

6.3 Future Work

While the current study demonstrates the feasibility of integrating federated learning with explainable AI for wearable stress tracking, several avenues remain available for research in the future. Firstly, expanding the dataset by enrolling a larger and more diverse group of participants would make the model more generalisable as well as resilient. Performance testing in real-world settings would be possible with real-time distribution to devices like fitness bands or smartwatches. Furthermore, the accuracy of stress classification and noise tolerance may be enhanced by multimodal sensor signal fusion, such as that between electrodermal activity (EDA), skin temperature, and breathing rate. From the algorithmic perspective, customized federated learning techniques might be achieved with future studies, whereby the models learn to adapt to individual baseline physiological patterns without compromising confidentiality. Explainability can be further improved by integrating natively interpretable components of models, such as attention layers, rather than applying post hoc XAI techniques. Finally, participatory design with Māori populations would ensure cultural safety, validate fairness in model predictions, and align system deployment with Te Mana Raraunga principles. All these advancements would enhance the ethics, technology, and clinical use of the system for broader real-world application. Future research can explore edge-optimized federated models and adaptive learning strategies, as proposed by Gao et al. (2023) and Ma & Lu (2022).

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Glossary

Term	Definition
PPG (Photoplethysmography)	A non-invasive method to measure blood volume changes, used in wearable health devices.
Federated Learning (FL)	A decentralized ML approach where models are trained locally on devices without sharing raw data.
Explainable AI (XAI)	Methods that make ML model decisions understandable to humans.
SHAP	Explains model predictions by showing each feature's contribution.
LIME	Explains individual predictions by approximating the model locally with a simple interpretable model.
RMSSD	A heart rate variability (HRV) metric indicating parasympathetic activity, linked to stress.

SDNN	An HRV metric showing overall variability, useful for stress analysis.
LF/HF Ratio	A frequency-based HRV metric indicating autonomic nervous system balance.
Cultural Safety	Respecting cultural identity in healthcare and research.
Data Sovereignty	Ownership and control over personal data, crucial in Māori and Indigenous contexts.
Health Information Privacy Code (2020)	NZ law regulating health data collection, storage, and use.
TensorFlow Federated (TFF)	Google's open-source framework for federated learning using TensorFlow.