Proactive Hydration Management through Wearable Sensors and AI

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Guide
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Introduction

Water Makes Up Most of the Body

Hydration is essential for health, performance, and preventing dehydration-related risks.

Traditional methods rely on thirst cues or manual tracking, which are often inaccurate.
Our solution uses wearable sensors to collect real-time physiological signals such as heart rate and skin conductance.

Machine learning models combine this data with demographic, activity, and environmental factors to predict hydration levels.

The system provides timely alerts and personalized recommendations to prevent dehydration.
Designed for both clinical and consumer use, it enables proactive hydration management anytime, anywhere.

Introduction(2)

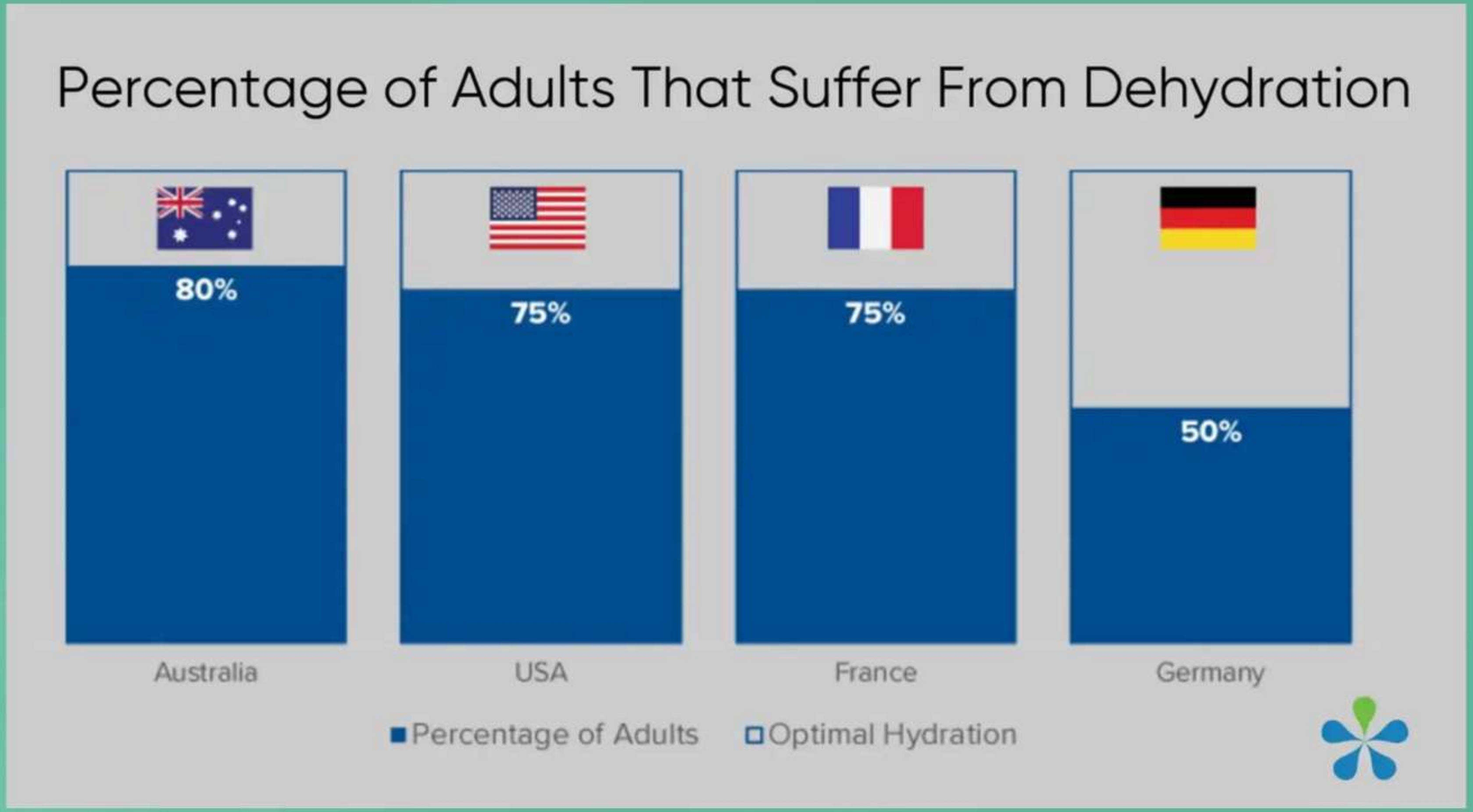
Water Makes Up Most of the Body

The table as follows may be used as a guide:

	% Body Fat Range	Optimal % total Body Water Range
Men	4 to 14 %	70 to 63 %
	15 to 21 %	63 to 57 %
	22 to 24 %	57 to 55 %
	25 % and over	55 to 37 %
Women	4 to 20 %	70 to 58 %
	21 to 29 %	58 to 52 %
	30 to 32 %	52 to 49 %
	33 % and over	49 to 37 %

Importance & Significance

- Prevents dehydration-related health risks before symptoms appear.
- Enhances athletic performance and recovery.
- Supports patient care in clinical settings.
- Promotes everyday wellness through proactive self-monitoring.
- Scalable solution for large populations using affordable wearables.



Literature Review

S.No.	Title	Authors/Source	Method / Technology	Key Insights
1	*An accurate wearable hydration sensor: Real-world evaluation of wearable body hydration monitor in 240 human participants*	Research study	Wearable hydration monitor tested on 240 participants	High accuracy, reliable, user-friendly, useful in clinical & daily life
2	*Recent Advancements in Wearable Hydration-Monitoring Devices*	Review paper	Biosensors, sweat analysis, optical devices	Highlights miniaturization challenges, improvements & future applications
3	*Wireless arm-worn bioimpedance sensor for continuous whole-body hydration monitoring*	Research article	Arm-worn wireless bioimpedance sensor	Reliable continuous monitoring, supports telemedicine & health tracking
4	*Wearable microfluidic biosensors with haptic feedback for continuous hydration monitoring*	Experimental study	Microfluidic biosensors with haptic feedback	Real-time hydration data, boosts user awareness, benefits sports & healthcare
5	*You can monitor your hydration level using your smartphone camera*	Research study	ML-based smartphone imaging	Non-contact, highly accessible, accuracy depends on lighting & calibration

Literature Review

S.No.	Title	Authors/Source	Method / Technology	Key Insights
6	*A New Method for Detecting Dehydration of the Human Body Using Non-Contact Millimeter Wave Radiometry*	Research article	Millimeter wave radiometry	Contactless & rapid dehydration detection for clinical & field use
7	*Noninvasive Monitoring to Detect Dehydration: Are We There Yet?*	Review article	Bioimpedance, sweat analysis, skin sensors (review)	Progress noted, but limitations persist; stresses real-world validation
8	*Personalized wearable electrodermal sensing-based human skin hydration tracking using machine learning*	Research article	Electrodermal sensors + ML algorithms	Personalized tracking, adapts to skin differences, improves accuracy
9	*Multispectral Sensor Fusion in SmartWatch for In Situ Skin Hydration Monitoring*	Research article	Smartwatch + multispectral analysis	Boosts accuracy, practical & accessible hydration monitoring tool
10	*Hydration status and physiological workload of UAE construction workers*	Field study	Hydration monitoring in construction workers	Links dehydration with workload & heat, recommends routine hydration checks

S.No.	Title	Authors/Source	Method / Technology	Key Insights
11	*Wearable sensor technology in sports monitoring*	Review article	Hydration sensors in sports wearables	Improves usability, accuracy, and athlete performance monitoring
12	*A study on isotonic hypovolemia in healthy adults using wearable bioimpedance sensor*	Clinical validation study	Bioimpedance sensor vs. clinical standards	Reliable detection of hypovolemia, applications in sports & acute care
13	*Development and analysis of a multi-wavelength near-infrared sensor for monitoring skin hydration*	Research article	Multi-wavelength NIR sensor	Improved sensitivity over single-wavelength, suitable for wearables
14	*Finger-actuated wireless-charging wearable sweat sensor system*	Research article	Sweat sensor + wireless charging	Convenient continuous monitoring; potential for consumer integration
15	*Bioelectrical Impedance to Estimate Changes in Hydration Status*	Review article	Bioelectrical impedance methods	Summarizes device advances & protocols, refinement needed for wide adoption

S.No.	Title	Authors/Source	Method / Technology	Key Insights
16	NoSQL database education: A review of models, tools and techniques	ScienceDirect (2025)	Survey and comparative analysis of educational models/tools	Highlights best practices and challenges for integrating NoSQL in higher education curricula; outlines necessary skills for data modeling and database management
17	*Automatic NoSQL to Relational Database Transformation with Dynamic Schema Mapping*	Wiley (2020)	Algorithmic transformation, schema mapping	dynamic schema mapping approach, enabling seamless data migration from NoSQL to RDBMS; supports hybrid data analytics workflows
18	*A Study of Big Data and Classification of NoSQL Databases*	IEEE Xplore (2020)	Classification and comparative study	Systematically classifies NoSQL databases (document, key-value, column, graph); assists practitioners in selecting suitable models for specific big data scenarios
19	*An ontology-based approach to designing a NoSQL database for semi-structured and unstructured health data*	PMC/NLM (2023)	Ontology-based schema design	Applies ontology methods for improved schema flexibility and integrity; supports complex healthcare data integration and management
20	*Innovations in NewSQL and NoSQL for High Scalability and Security*	IJRPR (2025)	Review of technical innovations	Reviews recent advances in scalability, multimodel architectures, and AI-driven

Literature Survey Findings

1. Themes Discovered in Review

- **Wearable Sensors & Non-invasive Methods:** The field is advancing with new wearable sensors and non-invasive techniques for monitoring hydration.
- **Real-Time Tracking:** There's a major trend towards continuous, real-time tracking of body water levels using biosensors, bioimpedance devices, and smartphone tools.
- **Personalization & AI:** Usability and personalization are top priorities, with machine learning being used to tailor hydration monitoring.
- **Broad Applications:** These new technologies are being validated for use in various settings, including clinical, sports, and occupational environments.
- **Increased Accessibility:** Devices like smartwatches, wireless systems, and microfluidic biosensors are making hydration tracking more accessible for everyday, real-world application.

Literature Survey Findings(2)

2. Identification of Gaps Based on Current Scenario/Industry Trends

- **Standardization:** Standardized protocols for testing and implementation are missing.
- **Long-Term Reliability:** The long-term durability and reliability of these devices remain a concern.
- **Accuracy Issues:** Maintaining accuracy under varying real-world conditions is an ongoing problem.
- **Miniaturization & Integration:** Further work is needed on sensor miniaturization and seamless integration into existing healthcare systems.
- **Interoperability:** The industry needs interoperable platforms that can work with different devices and systems.
- **Data Privacy:** Strong data privacy and security measures are essential but not yet fully addressed.
- **Affordability:** There is a need for more affordable devices to reach the consumer market.
- **Deployment Stage:** Most innovations are still in the prototype stage and have not achieved regulated, widespread deployment.

Scope and Challenges

Scope

Current hydration monitoring is reactive, relying on thirst cues and manual checks. There is a need for a real-time, non-invasive, and predictive system to prevent dehydration in everyday and clinical settings.

Research Challenges

- Accurate prediction from noisy wearable sensor data
- Integrating multi-modal data (physiological, demographic, environmental)
- Real-time analysis with minimal latency
- Personalization for diverse users and conditions

Problem Statement

Research Objective

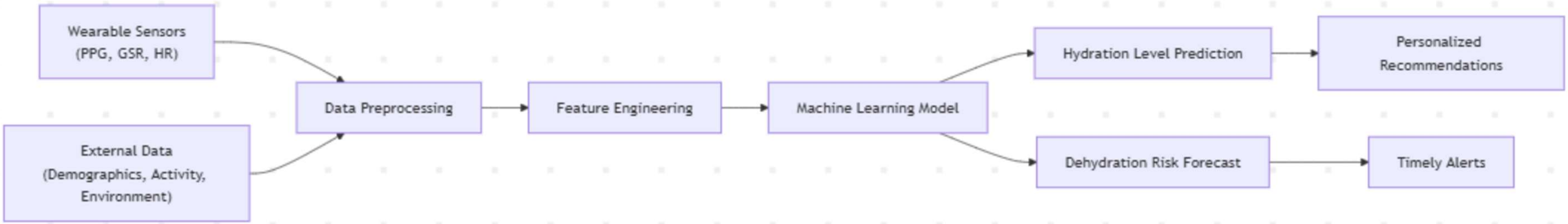
To develop an AI-powered wearable system that predicts hydration levels in real time and provides timely, personalized alerts to prevent dehydration.

Key Contributions

- Create a predictive AI model to analyze sensor data and estimate the user's hydration status in real time.
- Implement a personalized alert system that provides timely and actionable hydration recommendations.
- Validate the system's accuracy and effectiveness against standard clinical methods in diverse user groups.

Methodology

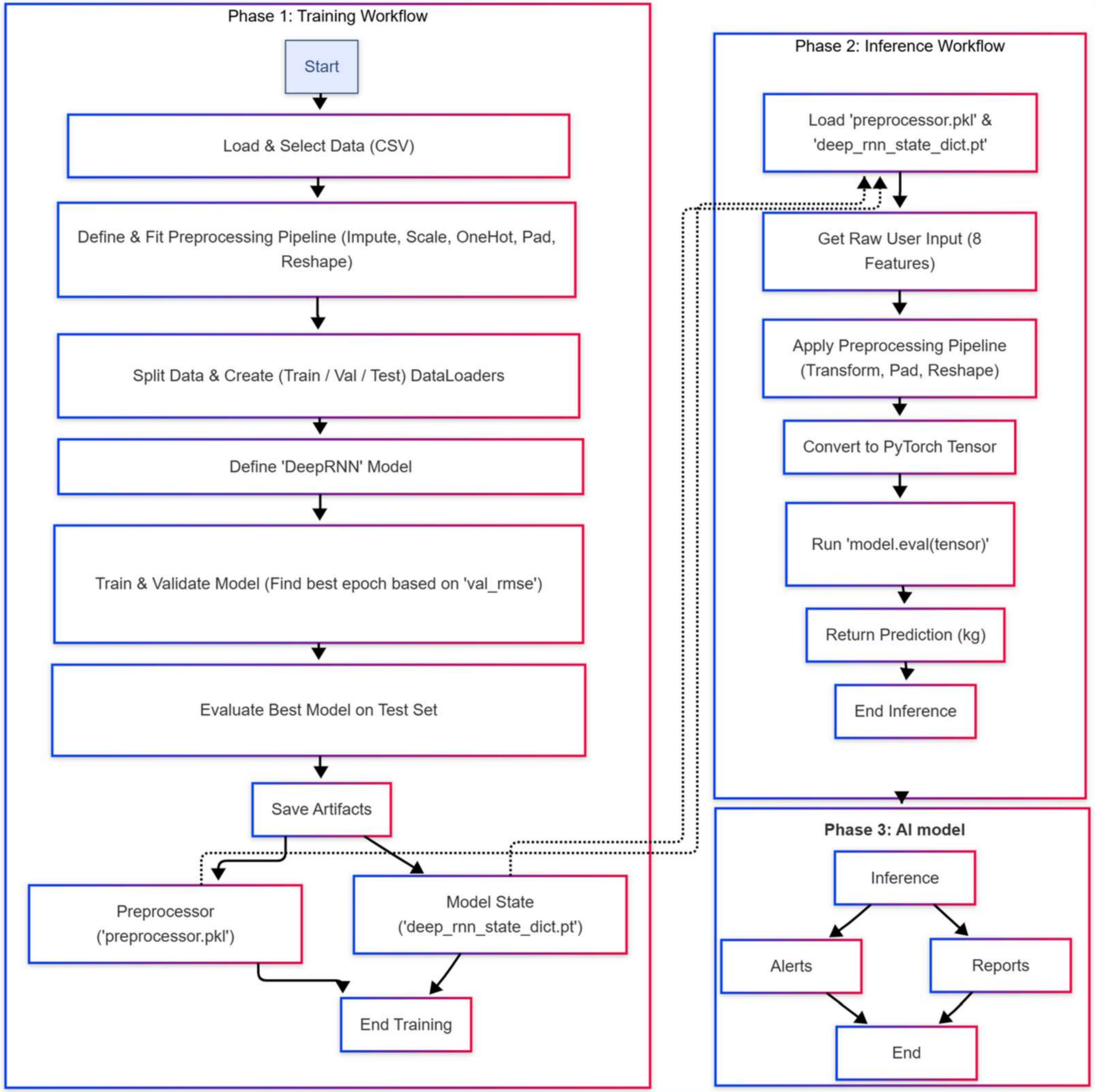
1. **Data Collection** – Gather physiological signals, demographic info, activity, and environmental data from wearables.
2. **Preprocessing** – Clean, synchronize, and transform data for analysis.
3. **Model Development** – Train ML models to predict hydration levels and forecast dehydration events.
4. **Integration** – Deploy on wearable devices for real-time monitoring.
5. **Evaluation** – Benchmark performance using validated hydration datasets.



Proposed System

AI/ML Workflow

1. The diagram shows a complete machine learning lifecycle, split into "Phase 1: Training" and "Phase 2: Inference."
2. **Phase 1** details loading data, preprocessing it, and training a 'DeepRNN' model to find the best version.
3. Training saves two key artifacts: the preprocessor.pkl and the model weights (deep_rnn_state_dict.pt).
4. **Phase 2** loads these artifacts to process new user input (8 features) and generate a final prediction (kg).
5. **Phase 3** indicates the model's output is then used to create "Alerts" and "Reports."



Dataset

The **SpectroPhon DBM** dataset, which contains raw data from **240 volunteer human subjects** collected during a 90-minute physical activity regimen to validate hydration monitoring, is publicly available. You can access and download the dataset from the following official link:

Mendeley Data: SpectroPhon DBM Subject Data
https://data.mendeley.com/datasets/jt22782wjh/1

The dataset includes measures such as body mass loss (water mass loss) corrected for water consumed, along with device-recorded perspiration volume and additional physiological parameters. This open resource is directly relevant for developing and benchmarking predictive hydration models

Dataset(2)

Subject no. 6										
Gender	female	Age	32		name	Sarah Hofmann				
	1	2	3	average	Gear s2		Gear fit 2		water	
initial	61.95	61.95	61.95	61.95	Accumulated sweat	Salt lost	Accumulated sweat	Salt lost	531	salt reference
resting 1	61.95	61.95	61.95	61.95	0.107	117.715	0.121	133.116	412	135.1055019
resting 2	61.9	61.9	61.95	61.91667	0.188	206.826	0.2	220.027	289	318.0493176
final	62.05	62	61.95	62	0.39	429.053	0.367	403.75	74	447.3075966
					total weight loss	difference with Gear s2 %	difference with gear fit 2 %		salt difference with gear s2 %	salt difference with gear fit 2 %
					0.407	4.176904177	9.828009828		4.080994104	9.737727902

Sample from the dataset

Dataset(3)


```
{
  "subject_id": 6,
  "name": "Sarah Hofmann",
  "gender": "female",
  "age": 32,
  "measurements": {
    "weight_kg": {
      "initial": {
        "readings": [61.95, 61.95, 61.95],
        "average": 61.95
      },
      "resting_1": {
        "readings": [61.95, 61.95, 61.95],
        "average": 61.95
      },
      "resting_2": {
        "readings": [61.9, 61.9, 61.95],
        "average": 61.91667
      },
      "final": {
        "readings": [62.05, 62, 61.95],
        "average": 62
      }
    },
```

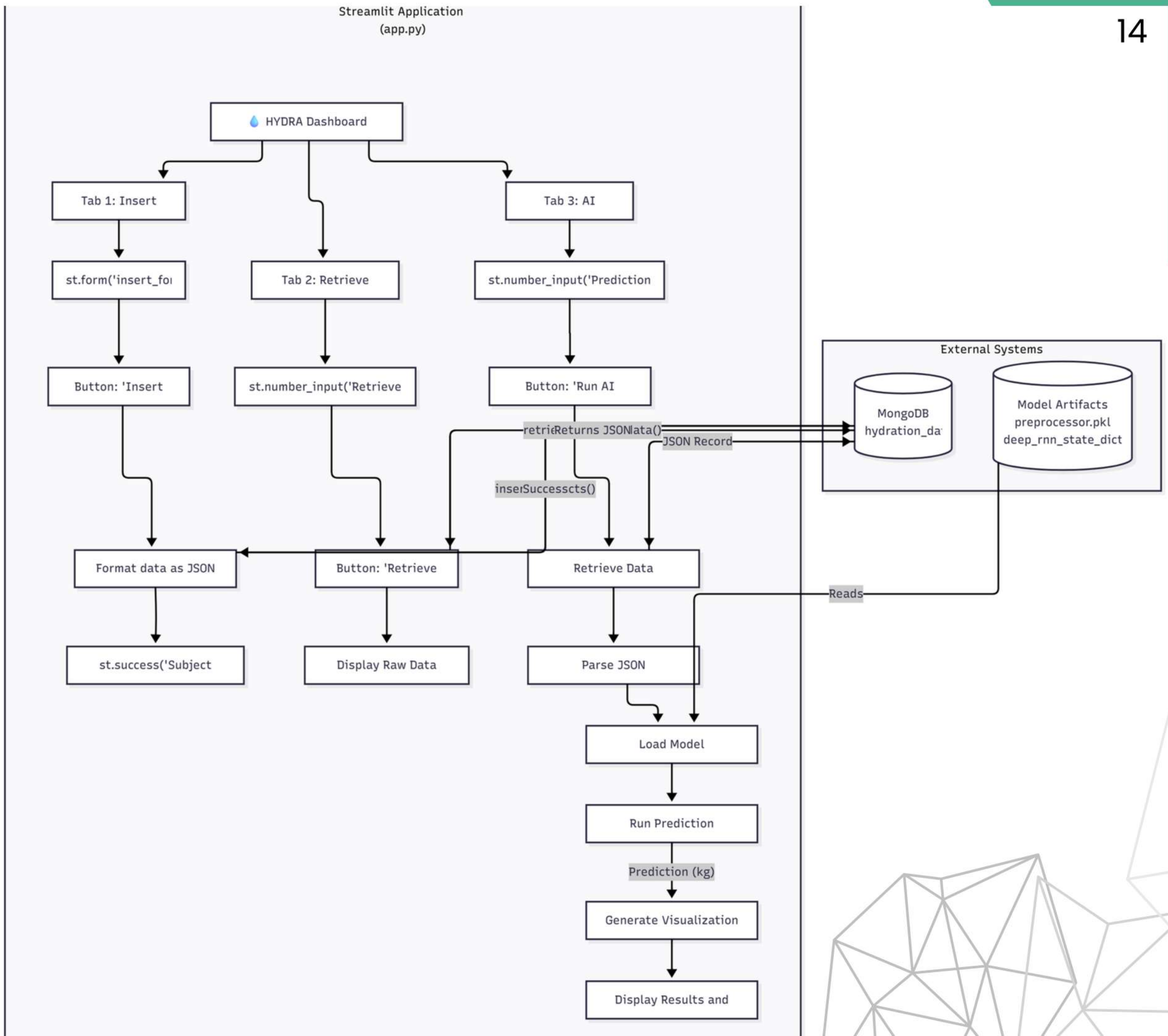

Stage	Avg Weight (kg)	Gear s2 Acc. Sweat	Gear s2 Salt Lost	Gear fit 2 Acc. Sweat	Gear fit 2 Salt Lost	Salt Reference
initial	61.95	NaN	NaN	NaN	NaN	531
resting 1	61.95	0.107	117.715	0.121	133.116	412
resting 2	61.91667	0.188	206.826	0.200	220.027	289
final	62.00	0.390	429.053	0.367	403.750	74

MongoDB Document → Pandas Dataframe

Modules

The Main Application has 5 major modules that form a flexible and scalable system architecture for the wearable and mobile devices:

1. **Data Ingestion Module**
2. **Data Retrieval Module**
3. **Visualization & Reporting Module**
4. **Inference Module**
5. **Main driver module**



Modules (2)

The Main Application has 5 major modules that form a flexible and scalable system architecture for the wearable and mobile devices:

1. **Data Ingestion Module**
2. **Data Retrieval Module**
3. **Visualization & Reporting Module**
4. **Inference Module**
5. **Main driver module**
6. **External Systems**

- **Data Ingestion Module:** It uses a Streamlit form (st.form) to collect new subject data from the user. Upon submission, it formats this data into a JSON document and saves it to the external MongoDB database.
- **Data Retrieval Module:** Its function is to look up existing data. The user inputs a Subject ID, and the application fetches the corresponding raw JSON record from MongoDB and displays it on the screen.
- **Visualization & Reporting Module:** After the inference module generates a prediction, this module takes that output, creates a graphic using make_water_loss_viz, and displays the complete results to the user (e.g., st.success for the prediction, st.image for the visual, and st.warning for alerts).
- I**nference Module:** It's a multi-step workflow that first retrieves a subject's data from MongoDB (like the Retrieval module), parses that JSON into a DataFrame, loads the saved preprocessor.pkl and deep_rnn_state_dict.pt from the Model Artifacts, and finally runs the prediction.
- **Main driver module:** This is the "Streamlit Application (app.py)" itself. It acts as the central container that launches the "HYDRA Dashboard" and uses st.tabs to organize all the other modules (Ingestion, Retrieval, and Inference) into a single, cohesive user interface.
- **External Systems:** This block represents the components that exist outside the application. It includes the MongoDB database, which stores and provides all the subject records, and the Model Artifacts store, which holds the pre-trained .pkl and .pt files needed for the inference module to function.

Deep RNN model

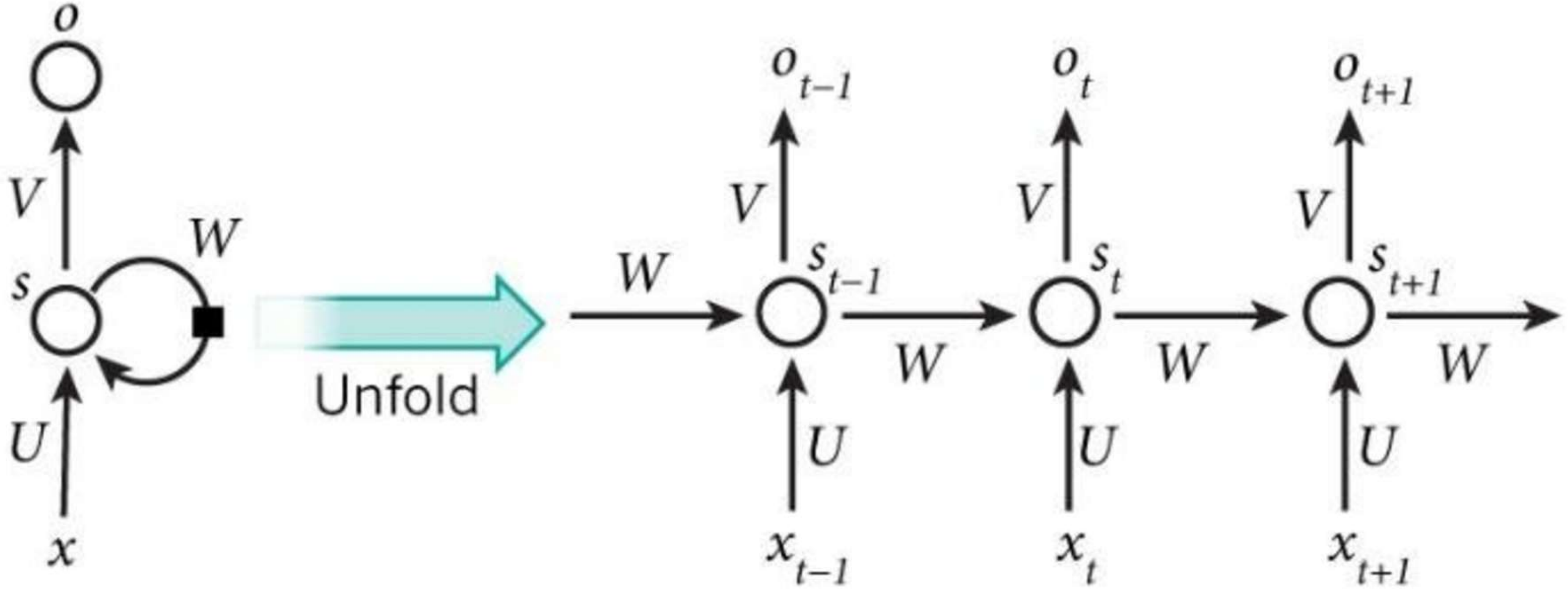
The core RNN equations are for calculating the hidden state and the output at each time step. The hidden state is a function of the current hidden state. A common formulation is **ht=σ(Whht-1+Wxxt+bh)h** sub t equals sigma open paren cap W sub h h sub t minus 1 end-sub plus cap W sub x x sub t plus b sub h close paren

$h_t=\sigma(W_h h_{t-1}+W_x x_t+b_h)$

and yt=σ(Wyht+by)y sub t equals sigma open paren cap W sub y h sub t plus b sub y close paren

$y_t=\sigma(W_y h_t+b_y)$

$$\begin{aligned} \boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} \\ \boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\ \boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)} \\ \hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)}) \end{aligned}$$



Results

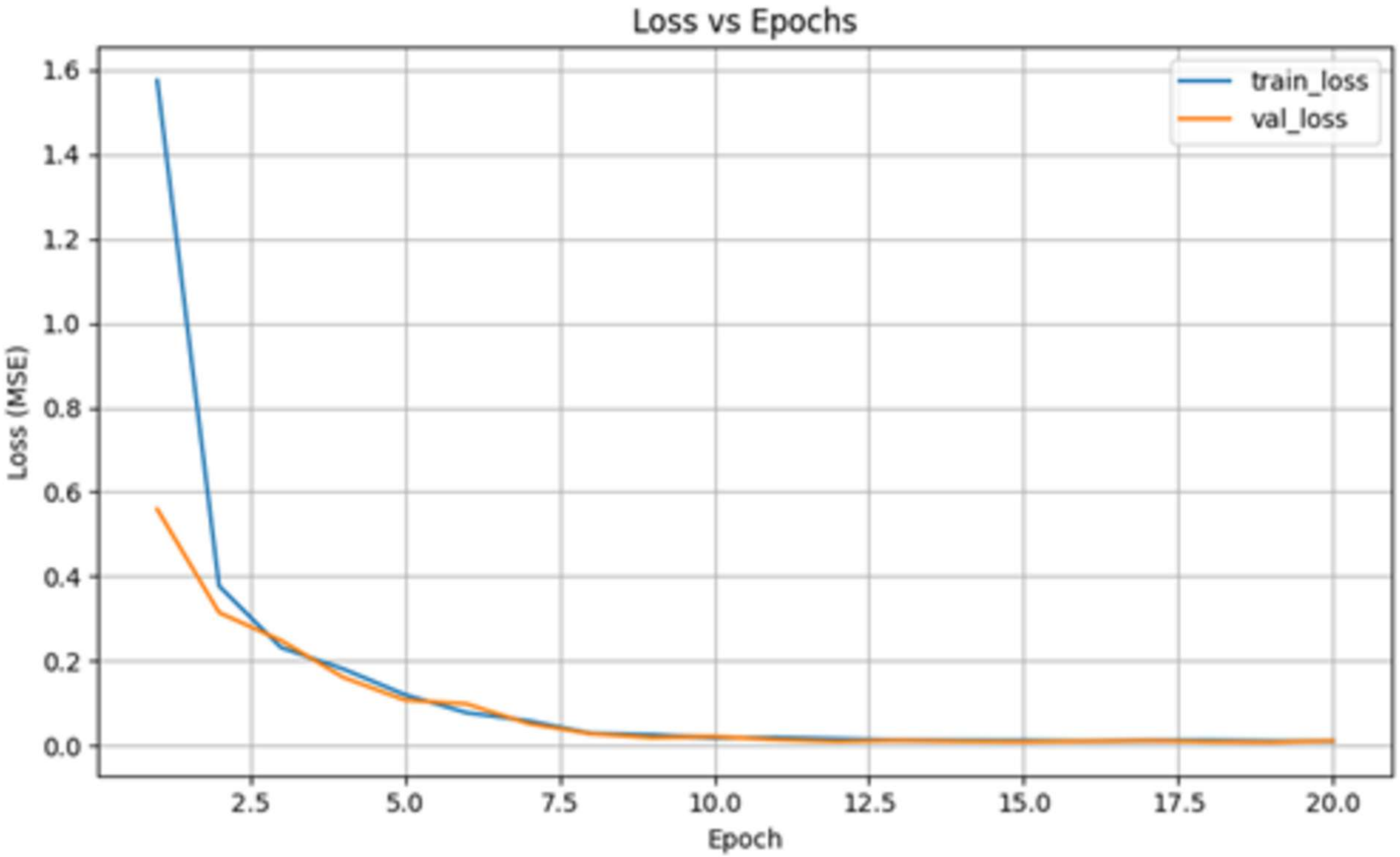
The predictive capabilities of the models were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) on the test dataset. Classical regression models, including Linear Regression and Random Forest, served as baselines. The DeepRNN outperformed these models significantly, achieving an RMSE of 0.0085 kg, MAE of 0.0654 kg, and an R^2 of 0.9513, indicating high prediction accuracy.

Accuracy Compared to other models

Model	RMSE	MAE	R^2
Ridge Linear Regression	0.00704	0.05518	0.95986
PyTorch_DeepNN	0.00903	0.07101	0.94853
RandomForest	0.00980	0.06372	0.94409
MLPRegressor	0.03031	0.13999	|0.82713

Results (2)

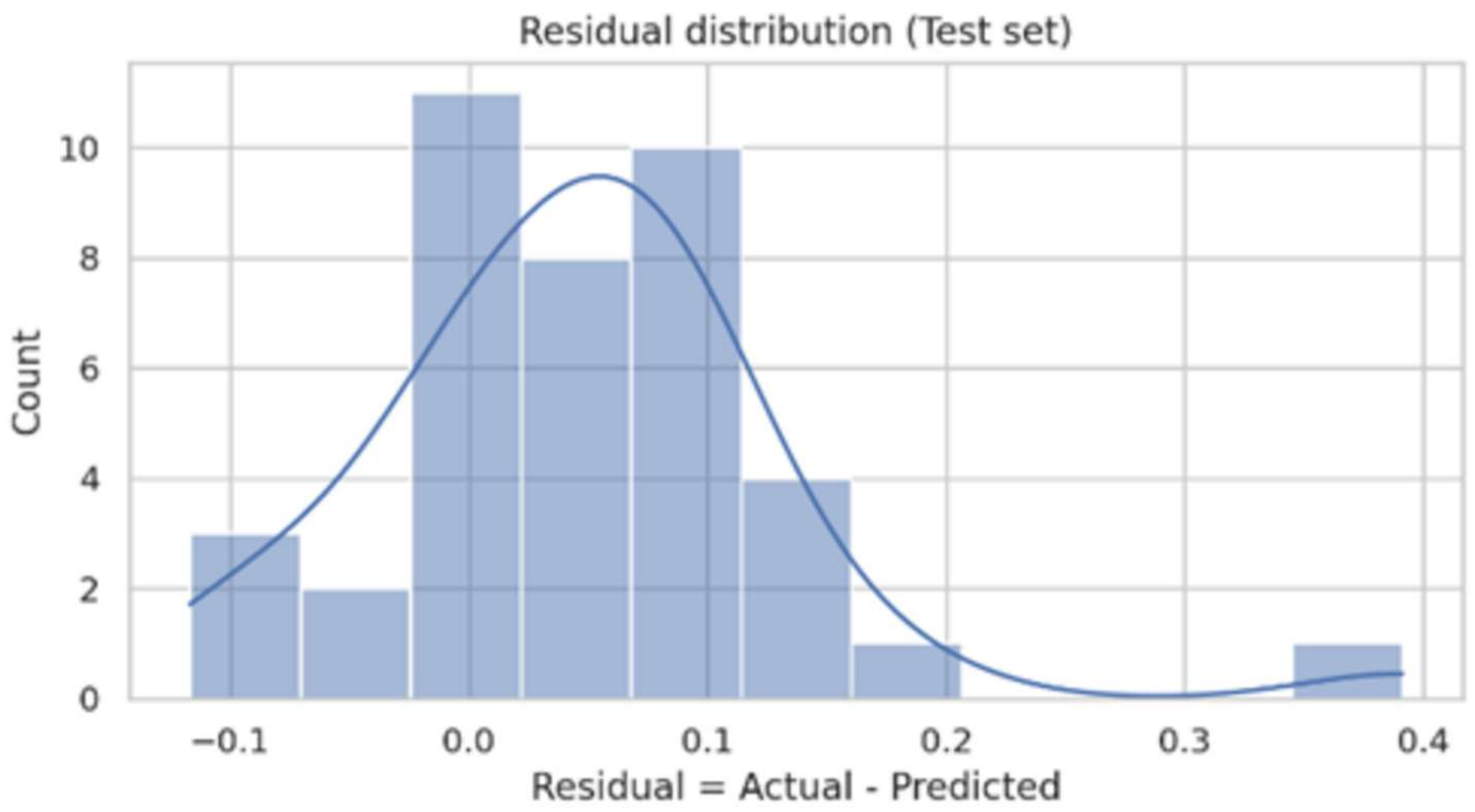
Training Accuracy and Validation

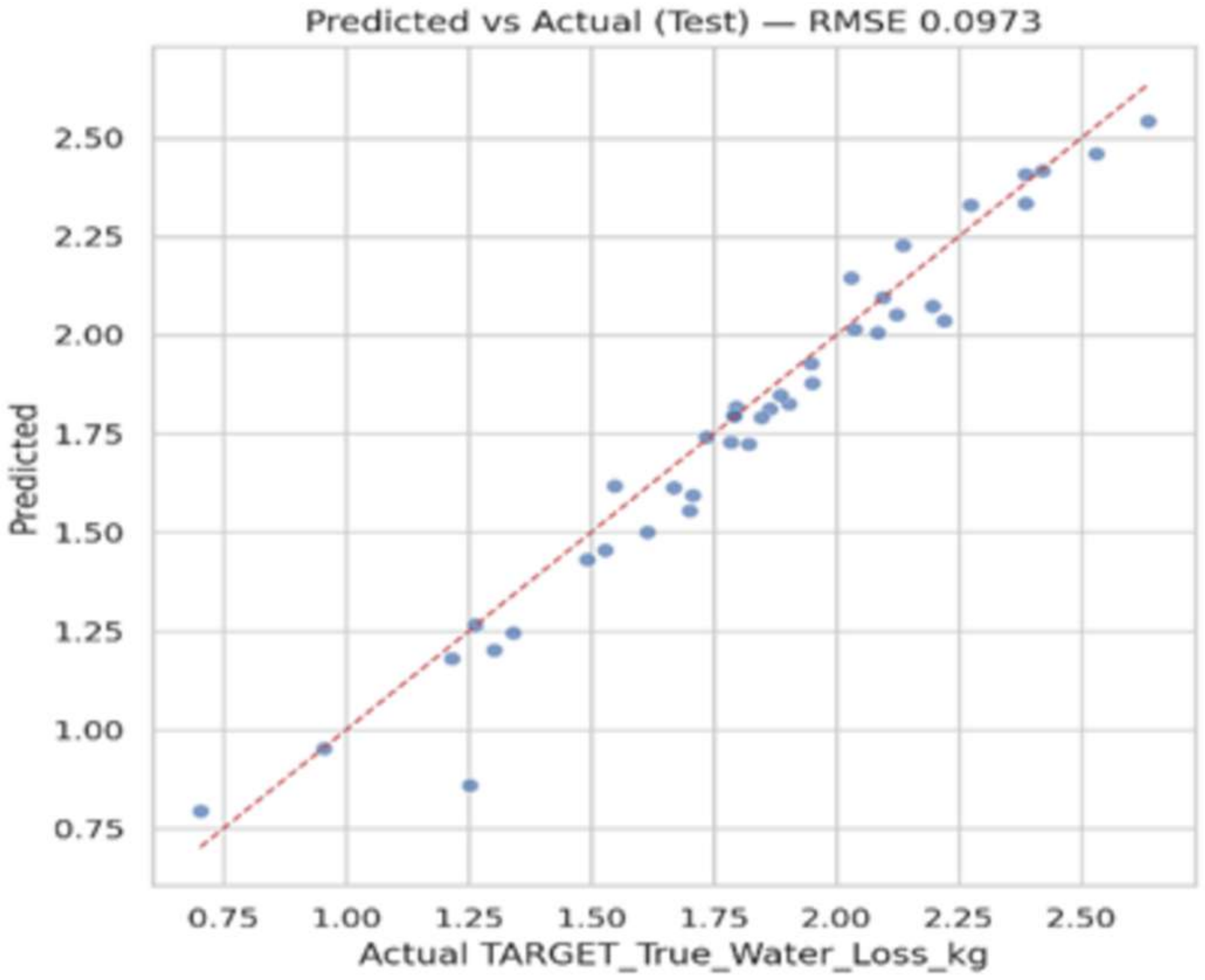


Training and validation loss vs. epoch Shows learning progress and checks for overfitting.

Results (3)

Testing the model





Attention-based and Residual RNN variants provided marginal improvements but increased training complexity, making DeepRNN the preferred balance between performance and efficiency.

Future Work

Future work will focus on integrating additional sensor modalities, such as bioimpedance and microfluidic sensors, to further enhance predictive accuracy.

- Integrate additional sensor modalities such as bioimpedance and microfluidic sensors to further enhance predictive accuracy.
- Prioritize deployment on edge devices for real-time, on-device inference to facilitate widespread consumer and clinical applications.
- Expand datasets to include diverse populations and environmental conditions to improve generalization.
- Explore hybrid models combining physics-based hydration models with deep learning techniques to improve interpretability and robustness, which will pave the way toward comprehensive health monitoring systems.

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