**You2.0 – Beyond Tracking, Into Becoming**

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*Submitted by*

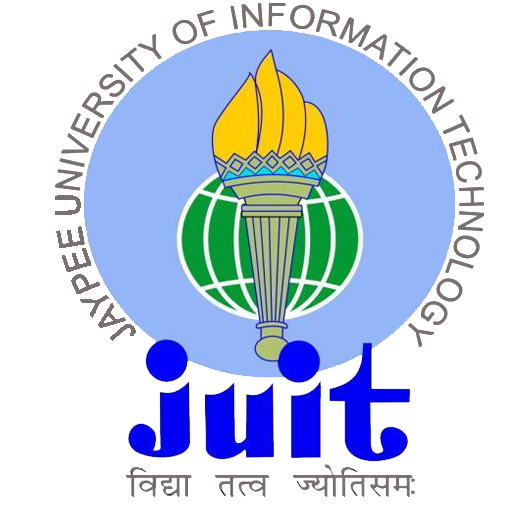
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**ABSTRACT**

In today's fast-paced world, people commonly struggle to maintain a healthy lifestyle due to irregular sleep cycles, bad eating habits, excessive sedentary hours, and insufficient physical activity. These factors play an important role in lifestyle-related illnesses such as obesity, diabetes, hypertension, and chronic stress, which are now among the most significant health issues worldwide. According to World Health Organization study, noncommunicable diseases caused by poor lifestyle choices account for a large share of premature deaths each year, and the trend is steadily increasing.Despite increased knowledge, most people do not constantly analyze and review their everyday behaviors. Simple tasks such as tracking water consumption, sleep quality, and hours of inactivity are commonly disregarded, resulting in long-term health consequences that may have been averted with early intervention. While existing fitness programs and wearables offer partial solutions, they either focus on certain qualities such as step count or heart rate, make overly broad suggestions, or are prohibitively expensive for students and professionals who demand inexpensive and comprehensive tools. What is lacking is a complete, intelligent system that not only analyzes numerous lifestyle factors but also learns from user behavior to provide meaningful, personalized information.

To address this gap, the proposed project offers an AI-Powered Lifestyle & Wellness Tracker, a smart health companion that collects, analyzes, and interprets user data in meaningful ways. The system will use manual logging (for meals, hydration, and mood) and sensor-based tracking (for sleep, activity, and inactivity) to create a comprehensive picture of a person's daily routine. Using machine learning models trained on real-world health statistics, the application will identify patterns, detect potential dangers, and make targeted recommendations to lower the risk of lifestyle diseases. For example, the system can highlight obesity risks if prolonged sitting and unhealthy diet are identified, or warn users about stress and fatigue if sleep data consistently falls below recommended levels.Unlike generic health apps, this solution leverages real-time personalized notifications and gamified habit tracking to keep users interested. Suggestions such as "You've been inactive for two hours—take a short walk" or "Your water intake today is below average—drink a glass of water" can help you stay healthy all day. This project intends to help people manage their health, improve their lifestyle, and form long-term habits by combining AI-powered forecasts with engaging feedback and progress monitoring. Finally, it demonstrates how technology can be used as a proactive tool for reducing lifestyle disorders.

**Chapter 01: INTRODUCTION**

**1.1 Introduction**

Most of us find it difficult to maintain a good balance in today's fast-paced society; bad eating habits, prolonged sitting, erratic sleep patterns, and ongoing stress are all becoming commonplace. Obesity, diabetes, and hypertension— lifestyle disorders that are currently among the biggest worldwide health concerns—are closely related to these behaviors.

Although there are fitness devices and apps, they frequently fall short—either by concentrating primarily on heart rate or steps, providing general advice, or being excessively expensive.

Our project fills that need. The AI-powered Lifestyle & Wellness Tracker **You2.0: Beyond Tracking, Into Becoming** is intended to be more than a simple monitoring device. After creating a comprehensive picture of everyday activities through human logging and sensor-based tracking, it employs machine learning to identify potential hazards and provide tailored, real-time recommendations.

With tools like proactive health insights, gamified habit tracking, and intelligent reminders, You2.0 seeks to assist users in changing their lifestyles rather than merely monitoring them.

### **1.2 Problem Statement** Modern lives, characterized by inadequate sleep, unhealthy foods, prolonged sedentary behavior, and restricted physical activity, have contributed to a global increase in lifestyle-related disorders such as obesity, diabetes, hypertension, and chronic stress. Despite improved awareness, many people fail to consistently monitor their daily activities, resulting in preventable health problems. Existing options, such as fitness apps and wearables, either offer fragmented insights, lack customisation, or are too expensive for students and working professionals. There is an obvious need for an easily available, intelligent system that integrates many lifestyle indicators, analyzes patterns, and provides individualized, actionable feedback in real-time.

**1.3 Objective**

* To create a system that records lifestyle data (diet, sleep, physical activity, hydration, and mood) using manual or sensor-based inputs.
* To develop and implement machine learning models that assess data and forecast potential health hazards (for example, obesity, stress, and diabetes).
* To encourage healthy habits, offer individualized, real-time suggestions and gamified habit tracking.
* To incorporate customized alerts and reminders that encourage people to make better choices all day long.
* To provide an intuitive mobile interface that makes tracking, data entry, and visualization fun and easy.
* To give consumers weekly or monthly reports with trend analysis and data-driven insights so they can recognize long-term trends in their lifestyle.

### **1.4 Significance and Motivation of the Project Work**

Lifestyle-related diseases are among the top causes of early death worldwide, accounting for a sizable portion of healthcare spending. Small daily habits, such as drinking water or taking inactive breaks, can have a significant impact on long-term health but are frequently overlooked. Current apps provide limited functionalities (such as step count) and fail to deliver comprehensive, tailored data.

This initiative is driven by the desire to enable people to take charge of their health in a proactive, cost-effective, and enjoyable way.

* The suggested solution combines AI-driven analysis, real-time nudges, and gamification to reduce the risk of lifestyle diseases.
* Encourage healthier daily routines through continuous feedback.
* Make wellness management available to students, young professionals, and the general public.

Finally, this study shows how technology may transition from passive tracking to active, intelligent coaching for long-term health improvement.

**1.5 Organization of Project Report**

The rest of the report is organized as follows: Chapter 02 presents the literature survey, covering existing works, key findings, and research gaps. Chapter 03 describes the system development, including requirements, tools, datasets, design, and models used. Finally, the References section lists the research papers and resources referred to in this work.

**Chapter 02:Literature Survey**

**2.1 Literature Overview**

| S. No. | Author &  Paper Title  [Citation] | Journal/  Conference (Year) | Tools/  Techniques/  Dataset | Key Findings/  Results | Limitations/  Gaps Identified |
| --- | --- | --- | --- | --- | --- |
| 1. | Chiam et al. – Co-Pilot for Health Personalized Algorithmic AI Nudging to Improve Health Outcomes[1] | arXiv Preprint (2024) | Wearables + AI nudging system; large-scale intervention (84,764 participants) | Increased daily steps by ~6.17% and MVPA by ~7.61% with AI nudges vs control | Limited to physical activity outcomes; does not cover diet, stress, or holistic wellness |
| 2. | JMIR Cardio – AI-Based, Autonomous, Digital Health Intervention Using Precise Lifestyle Guidance on Blood Pressure in Adults With Hypertension[2] | JMIR Cardio (2024) | BP monitor + wearable tracker + questionnaires + personalized ML models | Improved blood pressure control using AI-driven personalized guidance | .Non-randomized single-arm trial; results may lack generalizability |
| 3. | Stolfi et al. – Use of Non-Invasive Parameters and Machine Learning Algorithms for Predicting Future Risk of Type 2 Diabetes[3] | BMC Bioinformatics (2020) | ML models using non-invasive lifestyle & clinical data | Successfully predicted diabetes risk using ML | Dataset limited in diversity; model may not generalize |
| 4. | Patra et al. – Personal Goals, User Engagement, and Meal Adherence within a Personalised AI-Based Mobile Application for Nutrition and Physical Activity[4] | MDPI Life (2024) | AI-based nutrition & activity mobile app; engagement tracking | Personalized goal-setting improved user engagement and meal adherence | Study limited to short-term engagement; scalability not tested |

| 5. | Meta-analysis-The Effectiveness of Gamification in Changing Health-Related Behaviors: Systematic Review & Meta-analysis [5] | Systematic Review (2024) | Review & meta-analysis of gamification studie | Gamification increases engagement and improves outcomes like step counts | Many studies lacked long-term evaluation; focus mostly on physical activity |
| --- | --- | --- | --- | --- | --- |
| 6. | JMIR mHealth – Applying AI in the Context of the Association Between Device-Based Assessment of Physical Activity and Mental Health: Systematic Review [6] | JMIR mHealth (2025) | Review of device-measured activity + AI models | AI can link physical activity patterns with mental health insights | Few longitudinal studies; lack of standardized datasets |
| 7. | Straczkiewicz et al. - A systematic review of smartphone-based human activity recognition methods for health research [7] | npj Digital Medicine (2021) | Systematic review of 108 studies; Accelerometer, gyroscope, magnetometer sensors; Machine learning classifiers | Smartphones are well-suited for HAR research in health sciences. | Limited generalizability due to small sample sizes, homogeneous populations (primarily young adults), lack of diverse participants and activities. |
| 8. | Kundu et al. - Smartphone based human activity recognition irrespective of usage behavior using deep learning technique [8] | Int. j. inf. tecnol. (2025) | CNN-based HAR framework; 2-D frequency domain images; Real-life data from 4 devices. | Proposed ensemble CNN model achieved 94% accuracy even when training and test devices were different. | Limited to 4 basic activities (sitting, standing, walking, jogging); small dataset with only 8 users. |

| 9. | Wang et al. - The Impact of Gamification-Induced Users' Feelings on the Continued Use of mHealth Apps: A Structural Equation Model With the Self-Determination Theory Approach [9] | J Med Internet Res (2021) | Structural Equation Model; Self-Determination Theory; Survey of 307 mHealth app users; PLS-SEM analysis | Gamification significantly affects intrinsic motivation through autonomy (β=.312), competence (β=.346), and relatedness (β=.165). Intrinsic motivation positively impacts satisfaction (β=.311) and continuance intention (β=.142). | Limited sample size (307 responses from 2988 collected); focus on Chinese users only; limited exploration of different gamification elements; need for longitudinal studies to assess long-term effects. |
| --- | --- | --- | --- | --- | --- |
| 10. | Hwang et al. - Research Trends on Mobile Mental Health Application for General Population: A Scoping Review [10] | Int. J. Environ. Res. Public Health (2021) | Scoping review of 14 studies; Scottish Intercollegiate Guidelines Network (SIGN) checklist for quality assessment | Mobile mental health apps were effective in reducing stress, depression, and anxiety while improving well-being. Mindful meditation apps were most commonly used (35.7%). | Limited number of studies (only 14); most apps developed based on therapy rather than theoretical framework; lack of long-term effects studies. |
| 11. | Almuqrin et al. - Smartphone apps for mental health: systematic review of the literature and five recommendations for clinical translation [11] | BMJ Open (2025) | Systematic review of 31 studies; RCTs only; Risk-of-bias assessment using RoB 2 tool | Smartphone apps were generally effective and acceptable for mental health treatment. Apps showed effectiveness for treatment, self-monitoring, and multipurpose mental health interventions. | Homogeneous sample (primarily middle-aged women); 15 of 31 studies showed bias concerns; underrepresented demographics. |
| 12. | Gemesi et al. - Efficacy of an app-based multimodal lifestyle intervention on body weight in persons with obesity: results from a randomized controlled trial [12] | International Journal of Obesity (2024) | RCT with 168 participants; Oviva Direkt app; 12-week intervention with 12-week follow-up; BMI 30.0-40.0 kg/m² | ADHOC group achieved significant weight loss of 3.2±3.2 kg.Weight maintenance observed after 24 weeks. Time spent on app correlated with weight reduction. | Single-centre study in Munich region; 12-week intervention period may be too short; app usage decreased over time; limited to moderate obesity (BMI 30-40). |

| 13. | Birhanu et al. - A mobile health application use among diabetes mellitus patients: a systematic review and meta-analysis [13] | Frontiers in Endocrinology (2024) | Meta-analysis of 13 studies; Random-effects model; Joanna Briggs Institute critical appraisal tool | Pooled prevalence of mHealth app use for diabetes self-management was 35%. Future interest in using apps was 57%. Significant heterogeneity observed (I²=97.7%). | Significant heterogeneity among studies; limited to developed countries only; cross-sectional design prevents causal conclusions; geographic disparities in app usage patterns. |
| --- | --- | --- | --- | --- | --- |
| 14. | Hend S. Saad et al.- Employing of machine learning and wearable devices in healthcare system: tasks and challenges [14] | Neural Computing and Applications (2024) | No primary dataset; refers to reviewed datasets like MIT-BIH for arrhythmia | ML is crucial for remote patient monitoring, but faces significant challenges | Data reliability, security, high power consumption, and optimal model selection. |
| 15. | Jon N. Bondevik et al.- A systematic review on food recommender systems [15] | Expert Systems with Applications (2024) | Identifies common datasets: Allrecipes, Food, and Yummly | Most FRS use Content-based filtering with ML; few are truly personalized. | Small datasets, regional data imbalance, and lack of robust real-world evaluation. |
| 16. | Hafsa Habehh et al.- Machine Learning in Healthcare [16] | Current Genomics (2021) | ML algorithms (supervised, unsupervised, reinforcement) and their application in healthcare | Not a primary study; no dataset used. | ML has made substantial strides in predicting and identifying health emergencies and disease states |

| 17. | Logacjov A. et al.- *A Machine Learning Model for Predicting Sleep and Wakefulness Based on Accelerometry, Skin Temperature and Contextual Information[17]* | *Nature and Science of Sleep* (2024) | SVM, accelerometer + skin temp, 29 adults | Improved specificity (0.72) with high sensitivity (0.95). | Small dataset (29 participants), limited generalizability. |
| --- | --- | --- | --- | --- | --- |
| 18. | Qi An et al.- *A Comprehensive Review on Machine Learning in Healthcare Industry: Classification, Restrictions, Opportunities and Challenges* [18] | Sensors( 2023) | discusses classification, anomaly detection, clustering | ML improves diagnosis, treatment, and data-driven healthcare insights; supervised methods excel in prediction tasks, unsupervised useful for clustering | Requires large labeled datasets, risk of bias, ethical/data privacy issues, limited interpretability of unsupervised models |
| 19. | Tagne Poupi Theodore et al.- *Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Nutrition: A Systematic Review [19]* | *Nutrients* (2024) | PRISMA + SLR, 2019–24 papers | AI aids dietary assessment, personalization, disease prediction. | No standard datasets, limited clinical trials. |
| 20. | Raciel Yera et al.- *A Systematic Review on Food Recommender Systems for Diabetic Patients [20]* | *IJERPH* (2023) | PRISMA, RS methods, literature survey | Identified gaps in diabetic-focused recommender systems. | Few diabetes-specific RS, scarce real-world validation. |

**2.2 Key Gaps in the Literature**

* Limited Personalization: Most apps and systems do not fully adapt to individual habits, culture, or medical history.
* Integration Challenges: Multi-source data (activity, diet, sleep, mood) rarely combined into a single predictive framework.
* Long-Term Behavior Change: Gamification improves short-term engagement, but sustained health behavior change is underexplored.
* Regional & Cultural Coverage: Food recommender systems often ignore local diets, reducing adoption.
* Data Reliability: Self-reported and device-collected data inconsistencies affect model accuracy.
* Clinical Validation: Few AI interventions are clinically validated or scalable for real-world healthcare.
* Mental Health Integration: Limited studies simultaneously monitor physical activity and mental health effectively.
* Explainability & Ethics: ML models often lack explainability, raising ethical and privacy concerns.

**Chapter 03: System Development**

**3.1 Requirements and Analysis**

**Tools**

* **pandas 2.2, numpy 1.26** → dataset preprocessing & feature extraction
* **Matplotlib 3.9 / Seaborn 0.13** → visualizations
* **Draw.io**  → architecture diagrams
* **Google Docs / MS Word 2025** → documentation & reports

**Technologies:**

* **React Native 0.76** - mobile app development
* **Node.js 20 LTS + Express.js 4.21** - backend APIs
* **MongoDB Atlas 7.0 + Mongoose 8.6** - NoSQL database
* **JWT Authentication (jsonwebtoken 9.0.2)** - secure login
* **Firebase Cloud Messaging v12.0 / OneSignal 5.0** - push notifications
* **TensorFlow 2.16 / Keras 3.4** - LSTM, CNN, DeepSleep framework
* **scikit-learn 1.5** - baseline ML models, ensemble learning
* **Hugging Face Transformers 4.44** - mood detection (text/emotion)
* **OpenCV 4.10** - food recognition & portion estimation
* **ONNX Runtime 1.20 / TensorFlow Lite 2.16** - model deployment on mobile
* **Google Fit API** - step count & sleep tracking (alternative to sensors)
* **GitHub**  - version control

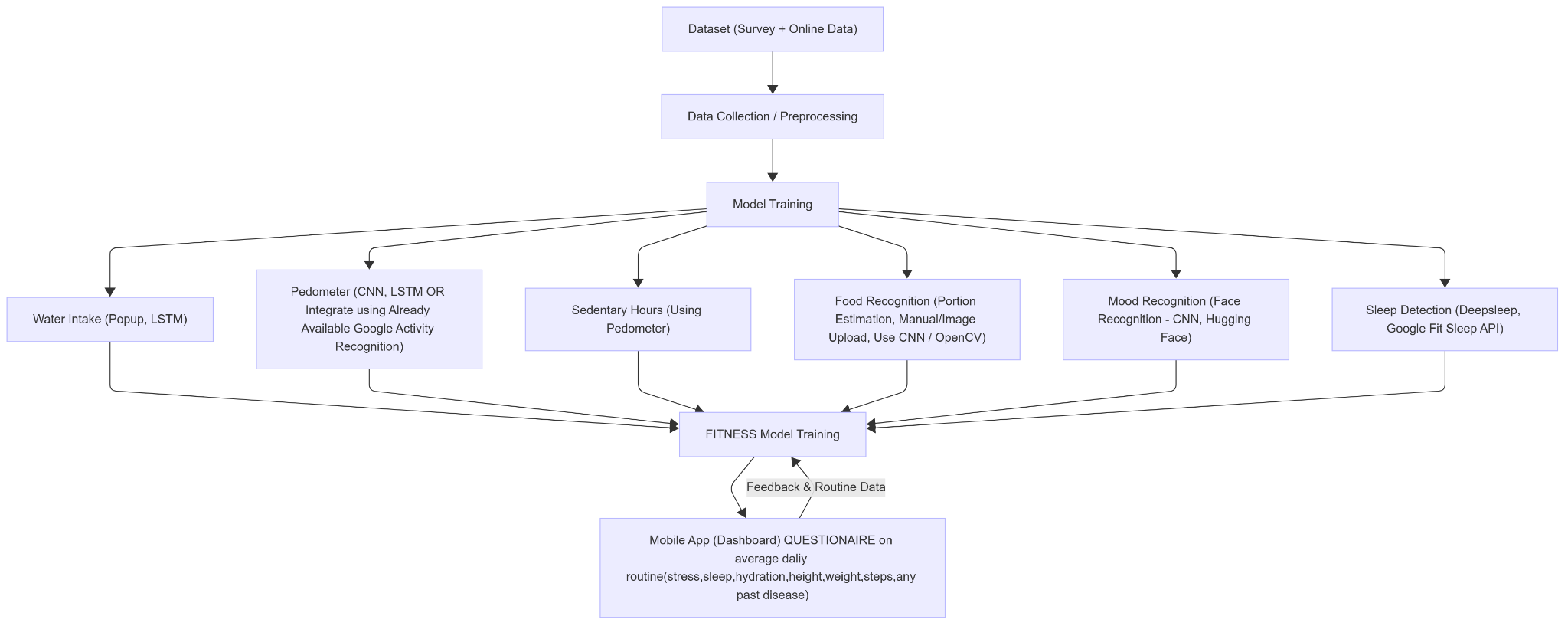
**Dataset**

* **Primary:** Google Form *“Daily Wellness Check-In”* — self-reported lifestyle, nutrition, sleep, mood, and activity data.
* **Secondary:** Food image datasets for portion detection: **Food-101** (101 categories) and **IndianFood16** (16 Indian cuisines).

**Key Features:**

* **Demographics:** Age, Gender, Occupation, Weight, Height
* **Sleep & Mood:** Sleep hours & quality, Fatigue, Emotional state, Stress
* **Diet & Nutrition:** Water intake, Meal quality, Number of meals, Food images/labels
* **Physical Activity:** Activity level, Steps, Exercise frequency, Sedentary hours
* **Medical History:** Diabetes, Obesity, Hypertension, Heart Disease, etc.

**3.2 PROJECT DESIGN & ARCHITECTURE**

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### **1. Dataset (Survey + Online Data)**

* **Source**: The system starts with datasets collected from:
  + Surveys: Questionnaires filled by users about their health, lifestyle, and routines.
  + Online Data: Publicly available fitness/health datasets (e.g., food calorie databases, sleep tracking datasets, mood recognition datasets).
* **Purpose**: To provide ground-truth data for model training and validation.

### **2. Data Collection / Preprocessing**

* **Preprocessing Steps:**
  + Cleaning raw survey data (removing null values, normalizing scales).
  + Data augmentation for image-based models (food images, facial emotion data).
  + Feature engineering (step counts, hydration levels, sleep hours, stress levels).
  + Normalization of numerical values (height, weight, calorie intake).
* **Purpose: Prepares data in a usable format for machine learning.**

**3. Model Training**

The system trains different models for various aspects of health and lifestyle monitoring**.**

#### **A. Water Intake (Popup, LSTM)**

* Popup reminder for hydration are based on:  
  + LSTM (Long Short-Term Memory) networks to predict hydration needs using user’s history (activity level, weather, previous intake).
* **Goal:** Encourage users to maintain optimal hydration throughout the day.

#### **B. Pedometer (CNN, LSTM or Google Activity Recognition)**

* **Methods:**
  + **C**NN (Convolutional Neural Networks) for sensor data recognition (classifying walking, running, idle).
  + LSTM to detect activity sequences over time.
  + Google Activity Recognition API (prebuilt solution).
* **Purpose:** To track steps, movement intensity, and classify activity types.

#### **C. Sedentary Hours (Using Pedometer)**

* Derived from step/activity data
* Identifies periods of inactivity (sitting/lying down) using pedometer/accelerometer readings.
* **Health impact:** Helps monitor risks of sedentary lifestyle (linked to obesity, diabetes, heart disease).

#### **D. Food Recognition (Portion Estimation using CNN/OpenCV)**

* **Methods:**
  + **CNN (Convolutional Neural Networks):** For image-based food classification (e.g., pizza, salad, rice).
  + **OpenCV:** For portion size estimation (measuring object size with reference).
  + **Manual entry option for accuracy.**
* **Purpose:** To estimate calorie intake and track diet quality.

#### **E. Mood Recognition (Face Recognition - CNN, Hugging Face)**

* **Face Recognition:** Detects the user's face.  
  + **CNN (Deep Learning)**: Identifies facial expressions (happy, sad, stressed).
  + **Hugging Face Models:** Pre-trained emotion recognition models (saves training time).
* **Purpose:** Helps monitor stress, mental health, and emotional well-being.

#### **F. Sleep Detection (Deepsleep, Google Fit Sleep API)**

* **Methods:**
  + **Deepsleep AI models:** Detect sleep stages (light, deep, REM) using wearable/smartphone data.
  + **Google Fit Sleep API:** Collects sleep logs from wearables/smart devices.
* **Purpose:** Tracks sleep duration and quality.

### **4. FITNESS Model Training**

* All individual models (hydration, steps, sedentary time, food intake, mood, sleep) are integrated into a central fitness model.
* **Goal:** To provide a holistic health profile and detect correlations (e.g., less sleep → higher stress; poor diet → more sedentary hours).

### **5. Feedback & Routine Data**

* User’s routine data and questionnaire feedback are continuously fed back into the system to improve model accuracy.
* **Adaptive personalization:** The more the user interacts, the better the recommendations.

### **6. Mobile App (Dashboard + Questionnaire)**

* **Dashboard:** Displays daily/weekly health insights (hydration, stress, sleep, steps, sedentary time).
* **Questionnaire:** Collects self-reported data:
  + Stress levels
  + Sleep hours
  + Hydration
  + Height, weight, BM
  + Daily steps
  + History of diseases
* **Purpose:** User engagement + extra ground-truth data for model fine-tuning.

## **End-to-End Workflow**

1. Collects data from surveys, sensors, and online datasets.
2. Preprocesses and trains specialized models (hydration, steps, food, mood, sleep)
3. Integrates all outputs into a fitness model.
4. Provides personalized recommendations via a mobile app.
5. Continuously learns from feedback and routine data.

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 *Review:* Summarizes activity recognition techniques using smartphones. Highlights accuracy and reliability challenges across varied user behaviors and devices.

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 *Review:* Proposes robust deep learning methods to recognize activity regardless of phone placement, improving real-world applicability.

[9] Wang et al., “The Impact of Gamification-Induced Users’ Feelings on the Continued Use of mHealth Apps: A Structural Equation Model With the Self-Determination Theory Approach,” 2020.  
 *Review:* Shows gamification enhances motivation and retention in health apps, emphasizing user psychology for sustained engagement.

[10] Hwang et al., “Research Trends on Mobile Mental Health Application for General Population: A Scoping Review,” 2022.  
 *Review:* Identifies trends in mental health apps; notes gaps in personalization and integration with healthcare systems.

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 *Review:* Highlights clinical translation challenges and emphasizes evidence-based app design for real-world efficacy.

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 *Review:* Validates app-based interventions for weight loss; underlines the importance of personalized recommendations.

[13] Birhanu et al., “A Mobile Health Application Use Among Diabetes Mellitus Patients: A Systematic Review and Meta-Analysis,” 2022.  
 *Review:* Demonstrates the effectiveness of mobile apps in improving glucose control and adherence in diabetic patients.

[14] Hend S. Saad et al., “Employing Machine Learning and Wearable Devices in Healthcare System: Tasks and Challenges,” 2020.  
 *Review:* Discusses the integration of ML and wearables; identifies technical and ethical challenges in large-scale deployment.

[15] Jon N. Bondevik et al., “A Systematic Review on Food Recommender Systems,” 2021.  
 *Review:* Reviews personalized food recommendation methods; highlights the gap in culturally-specific and regional diet modeling.

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 *Review:* Provides a broad overview of ML applications in diagnosis, monitoring, and predictive modeling.

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 *Review:* Demonstrates sleep/wake prediction using multi-sensor data; highlights accuracy improvements with contextual features.

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 *Review:* Reviews ML applications and limitations, emphasizing data quality and interpretability challenges.

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 *Review:* Shows AI’s potential in dietary analysis, personalized nutrition, and food image recognition.

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