
Journal of Informatics and Web Engineering

Vol. 5 No. 3 (October 2026)

eISSN: 2821-370X

Next-Gen Fitness: AI-Based Diet Plans and Real-Time Exercise Monitoring with Gradient Boosting, Gaussian Mixture Models and MediaPipe

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Abstract - Global shifts toward sedentary habits and refined dietary choices are magnifying public-health pressures from obesity, metabolic dysregulation, and cardiovascular disease, positioning targeted, personalized fitness coaching tools at the forefront of preventive-care strategy. By embedding tailored nutritional and physical-activity plans into daily life, these tools reinforce adherence, enhance intrinsic motivation, and catalyse sustained wellness achievements, each moderated by real-time analytics, feedback loops, and progressive adaptation to evolving behaviour and physiology. This manuscript proposes a comprehensive intelligent coaching architecture that combines probabilistic Gaussian Mixture Models (GMM) to cluster users by real-time activity and baseline health profile, fulfils dietary and regimen prescription by context-sensitive Extreme Gradient Boosted Trees, and pairs MediaPipe biosignal capture for on-spot performance diagnosis and postural adjustment. User-background information—age, weight, and unique preferences - flows into the platform and triggers tailored exercise plans that refresh automatically via the linked mobile app, ensuring routines stay fresh and relevant. Progress is recorded continuously, and instant feedback is given to maintain safety during workouts. When tested against varied datasets, the system delivers strong results: GMM clustering reaches 92% in segmenting users, XGBoost-based recommendations report 95% precision, 93% recall, and 94% F1-score for personalizing plans, and posture tracking powered by MediaPipe achieves 96% accuracy with minimal latency. Collectively, the metrics confirm the platform's effectiveness in fostering sustained and meaningful wellness engagement.

Keywords— *Fitness Recommendation System, Personalized Diet Plans, GMM Clustering, XGBoost, Real-time Exercise Tracking, Adaptive Recommendations, Health Monitoring*

Received: 14 June 2025; Accepted: 23 December 2025; Published: 16 October 2026

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1. INTRODUCTION

The rise of desk-bound work, along with habitual eating patterns, has turned manageable weight fluctuations into worrying epidemics, paving the way for obesity, hormone-based imbalances, and heart disease on a societal scale. To counter that proclivity, programs that personalize meals and exercise now play a frontline role in preventative medicine. The digital platforms provide each user with personalized calorie goals and workout plans. They increase motivation by increasing intrinsic motivation and supporting real and lasting progress. Fusion of Artificial Intelligence (AI) and Machine Learning (ML) scan and integrate data from wireless scales, activity logs, and biometric trackers. The resulting personalized coaching is agnostic to individual metabolism, workout, and stress engineered realities.

And obvious, systems of rules enormously oversimplified the processes of groceries, meals, and tailored meal plans towards the predefined goals of calorie consumption, dietary constituents, and algorithms built on rigid parameters. Further, attempts at battling the evolution of inertia and stagnating system based on data and pseudo-deductive rationale. Switching the participant with phantom biometric devices configured within the Medical Devices Internet framework allowed estimative algorithms to dynamically steer the configuration of meals. Currently, in the first place, practical clusters explore optimization cycles with deep and hybrid structures, testing great volumes of rigid public datasets with classified repositories integrating meals logs, dietary interactions simulating systematic of cohorts who helps to identify the agitation and the signals fundamental to itinerary and stagnation.

Simultaneously, fitness apps have created user-centric methods. There is proof that combining user-specific experiences with game-like features significantly improves prolonged attention, whereas ML models predict fitness routines, allowing actionable predictions. Meta-analyses focusing on adaptive learning and pose analysis highlight the advancement of computer vision for monitoring in near real-time, although occlusion and hardware limitations remain challenges. Compact neural architectures, pruned for mobile and wearables, now enable the tracking of activities in an energy-efficient manner, and ensemble models create robust pipelines for personalized recommendations while reducing user variations.

Nevertheless, most solutions exist in isolation—treating clustering, forecasting, and observation as discrete processes—thereby fragmenting the entire therapeutic cycle. This compartmentalization inhibits agility, weakens the capacity for instantaneous coaching, and stifles the synthesis of heterogeneous data types, thereby deferring the promise of fully integrated, continuous personalized health support.

To overcome remaining limitations, we present a cohesive AI-centered architecture that fuses Gaussian Mixture Models (GMM) for probabilistic user clustering, Extreme Gradient Boosting (XGBoost) for custom diet and exercise prescriptions, and MediaPipe-based computer vision for real-time motion analysis and postural correction. The system provides context-aware adaptive coaching that seamlessly integrates the three domains of clustering, forecasting, and surveillance as evidenced by real-time coaching based on user profiles, performance records, and progress trajectories.

2. LITERATURE REVIEW

The diet and fitness recommendation system has been transformed by the developments in AI and ML in recent years. Lopez et al. [1], in their article, reviewed the literature and described the role of AI in designing recommendation systems to foster active aging and healthy lifestyles. The survey by Tsolakidis et al. [2] points to the growing domain, indicating that hybrid AI, ethical constraints, and audiovisual integration will soon drive the next generation of fitness systems. Nagati [3] and Samy et al. [4] shift the focus to automated meal planning, primarily ML driven, where predictive modelling enhances compliance and the stabilization of eating behaviours.

Gamified design, smooth user flows, and spatial arrangement of graphical systems were supported by use after the initial engagement in the app as described by Hemaraju et al. [5]. The article by Siddhey et al. [6] discussed design adaptability and user-centric design features. As captured by Lu et al. [7], combining different models into ensembles improves the accuracy of recommendations for both diet and exercise, by providing tailored nudges for everyone.

Chen [8] evaluated the performance of supervised algorithms - decision trees, SVM, and deep networks—against the level of engagement with homework-out platforms, showing that all techniques achieved higher levels of

personalization, with the deep models performing the best. Widyawati et al. [9] implemented an improved version of K-Means clustering for the recommendations of malnourished toddlers. In Hong et al. [10], the use of adaptive GMM is described to enhance the prediction rate for health-related applications. In the work of Nilesh et al. [11], targeted investigations on real-time pose estimation within fitness contexts discovered that increases in accuracy are counterbalanced by persistent issues such as occlusions and lighting changes.

To blend healthcare more seamlessly, Armand et al. [12] quantified the positive impact of smart nutrition technologies combined with telemedicine, optimizing digital nudges over nutrition and longevity trajectories. Using these findings, Praveen et al. [13] developed a machine-learning driven platform to tailor and personalize nutrition advice and improved adherence by predicting individual specific adherence curves. Iwendi et al. [14] used and advanced the concept further by including IoMT sensor networks to provide real-time physiological data to augment and customize clinical recommendations beyond the guidelines. In a parallel approach, Toledo et al. [15] developed an adaptive engine which recommends food by balancing macronutrients and the subjective enjoyment of the meal, thus giving an operational, patient-centred interface to the clinical nutrition theory.

There is an increase in the sophistication of ML in fitness and nutrition. Fang et al. [16] showed that customizing exercise targets by individual capabilities and individual moods not only improves the adherence rate—subjects feel empowered instead of being overwhelmed—but also sustains motivation over weeks. In Forouzandeh et al. [17], the exercise of dual-attention heterogeneous graph networks used in the integration of consumption logs, biochemical parameters, and user preference to design menus that address mood and exercise need. Along this line, Rahmath Nisha et al. [18] created INAA, a mobile nutrition assistant that echoes real-life advice through logs of gastrointestinal, local ingredients, and cultural practices.

Min et al. [19] set out a wide-reaching framework with a focus on the granularity of personalization at the cultural and physiological levels and the ethical sourcing of the AI models as the most concerning and necessary unresolved challenges. More recently, Ispirova et al. [20] published the MsGEN benchmarking suite, designed to evaluate the generalizability of nutrient-value predictions across different recipe datasets. This addresses the generalizability challenges that arise in machine-learning applications in the food domain. Concomitantly, Chen and Guestrin [21] proposed the XGBoost framework, a highly scalable gradient-boosting framework and XGBoost's most used algorithm in dietary and fitness predictions due to its speed and high predictive accuracy. Ter et al. [22] used generative AI to develop a meal recommendation system integrated with chat-bot features.

In short, the progression in the literature is clear: initial systems used inflexible, preference-driven recommendations [3], [4], [5], [6]; these matured into Internet-of-Medical-Things-augmented setups [14] and clustering-based personalization [9]; the focus then shifted to adaptive models [10], heterogeneous graph approaches [17], ensemble learning techniques [7], and now a dedicated benchmarking suite [20] and integration chat-bot [22].

Contemporary research increasingly aims for real-time adaptability, personalization anchored to long-term health goals [12], and applications designed to foster preventive wellbeing. Despite notable progress, challenges remain in scalability, real-world validation, interpretability, and ethical governance, which future systems must address to ensure reliable, transparent, and user-trusted AI-driven diet and fitness recommendations. The summary of significant past effort is presented in Table 1.

3. RESEARCH METHODOLOGY

This study adopts a structured, data-driven pipeline for developing an AI-based fitness recommendation system. The pipeline consists of four stages: (i) data collection and preparation, (ii) model selection and training, (iii) system integration, and (iv) evaluation. A visual overview of the methodology is shown in Figure 1.

3.1 Data Collection and Preparation

The dataset for this research was built using a combination of primary and secondary data sources to ensure a balanced and representative sample. Primary data was gathered through a custom-designed mobile application, where participants voluntarily shared demographic and health-related details such as age, weight, height, BMI, dietary habits (e.g., vegetarian, vegan, keto, paleo), and fitness goals including weight reduction, muscle building, endurance training, or overall wellness. To supplement this, anonymized exercise logs (covering sets, repetitions,

and workout duration) and nutrition records (daily calorie intake and macronutrient breakdown) were incorporated from publicly available fitness repositories and health databases, consistent with earlier approaches in personalized fitness research.

Table 1. Summary of the Past Efforts

Ref.	Techniques	Features	Classifier/Models	Performance	Limitations
Samy (2024)	ML algorithms for diet recommendations	Basic personalization	SVM, Decision Trees, Neural Nets	~85% accuracy	Higher computation cost, limited real-time use
Widyawati (2025)	Clustering-based personalization	Optimization	K-Means	~88% clustering accuracy	Focused only on clustering, not real-time feedback
Chen (2021)	Fitness behavior prediction	Forecasting exercise routines	ML regression models	~87% predictive accuracy	Lacked integrated diet and posture monitoring
Nilesh (2022)	ML algorithms	Posture estimation	Multi-stage CNNs	89% tracking accuracy	Limited adaptability, no personalization of diet
Iwendi et al. (2020)	IoMT-assisted patient diet recommendation	Real-time dietary logs	Hybrid ML models	~82% accuracy	Focused mainly on diet, no exercise guidance

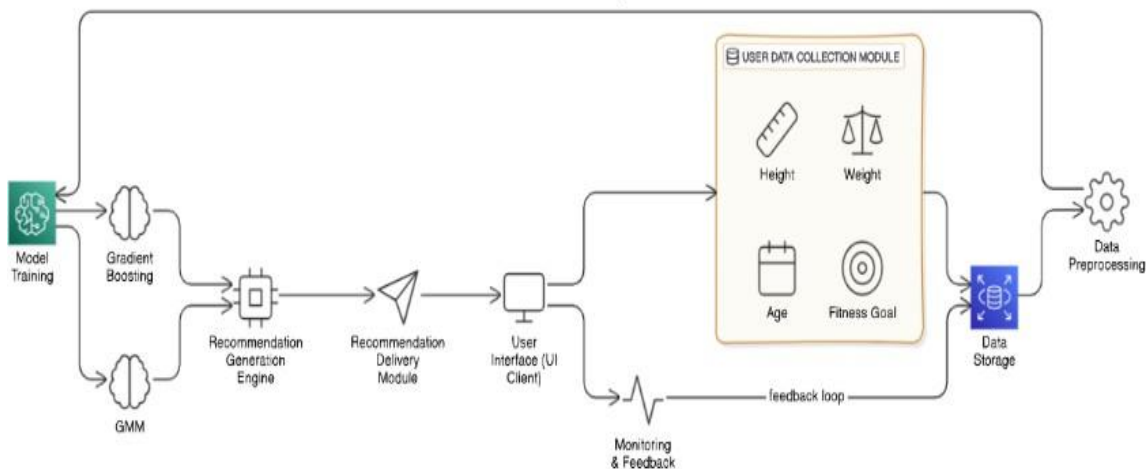


Figure 1. System Architecture of the Proposed Fitness Recommendation Framework

To address issues of class imbalance and to improve population diversity, synthetic user profiles were generated using open-access health surveys and nutrition datasets (e.g., NHANES and other public fitness databases). These generated profiles adhered to realistic distributions of anthropometric and lifestyle variables. The final dataset comprised approximately 5,000 unique user records as provided in Table 2. Before training ML models, a defined pre-processing workflow was applied as follows:

- **Normalization** – Continuous features such as age, weight, BMI, and workout duration were scaled to the range using Min–Max normalization.
- **Handling Missing Data** – Gaps in numerical features were filled using variable-wise mean values, whereas categorical features were completed using mode values.

- Categorical Transformation – Non-numeric variables such as dietary type, fitness status, and individual goals were converted into machine-readable one-hot encoded vectors.
- Feature Engineering – Postural information derived from MediaPipe’s human pose landmarks was structured into a feature set consisting of 33 key anatomical points, each represented by spatial (x, y, z) coordinates and visibility scores.

The processed dataset was then divided into training (70%), validation (15%), and test (15%) sets, following stratified sampling techniques reported in prior literature.

Table 2. Summary of the Dataset Attributes

Attribute	Type	Range/Values	Preprocessing Applied
Age	Numerical	18 – 65 years	Normalized (Min–Max)
Weight (kg)	Numerical	45 – 120 kg	Normalized (Min–Max)
BMI	Numerical	15 – 40	Normalized (Min–Max)
Fitness Level	Categorical	Beginner, Intermediate, Advanced	One-hot encoding
Dietary Preference	Categorical	Veg, Non-Veg, Vegan, Keto, Paleo	One-hot encoding
Goal	Categorical	Weight Loss, Muscle Gain, Endurance, Wellness	One-hot encoding
Exercise Logs	Numerical/Time	Sets, reps, duration (minutes)	Standardization, normalization
Posture Data (Landmarks)	Spatial coords	33 landmarks from MediaPipe (x,y,z + visibility)	Vectorized feature extraction

3.2 Machine Learning Models

The architecture merges a triad of models - GMM for data partitioning, XGBoost for tailored recommendations, and MediaPipe for real-time mobility assessment.

3.2.1 Gaussian Mixture Model (GMM)

GMM posits that observations are drawn from a finite collection of normal distributions. The Expectation-Maximization (EM) cycle iteratively evaluates responsibilities in terms of means, covariances and mixing coefficients (E step) and adjusts mixture parameters (M step) until convergence. Aligned with the below pseudo-code which stands for the GMM implementation for fitness prediction executed as following steps: first, import the GMM from the library called Scikit_learn. By next step, initialize the cluster size, covariance type and random seed. Upon completing the initialization, train the model and test sample result with highest posterior probability is assigned to the gaussian component. It yields probabilistic clusters, thereby surpassing K-Means where fitness tiers intercept.

Pseudo-code:

```

from sklearn.mixture import GaussianMixture
GMM = GaussianMixture(n_components=5, covariance_type='full', random_state=42)
GMM.fit(X_train)
clusters = GMM.predict(X_test)

```

3.2.2 Extreme Gradient Boosting (XGBoost)

XGBoost efficiently generates an ensemble of weak learners by sequential tree addition, maintaining L2 penalization against overly adaptive splits as given in Figure 2.

- Param suite (optimized via cross-validated grid): `n_estimators = 100`, `learning_rate = 0.1`, `max_depth = 5`, `reg_lambda = 1`.

- Task: Estimates caloric intake, assigns workout load, and formulates individualized schedules.
- Metric: Exhibits superior throughput and predictive quality in comparison with both Random Forest and Support Vector Machine routines.

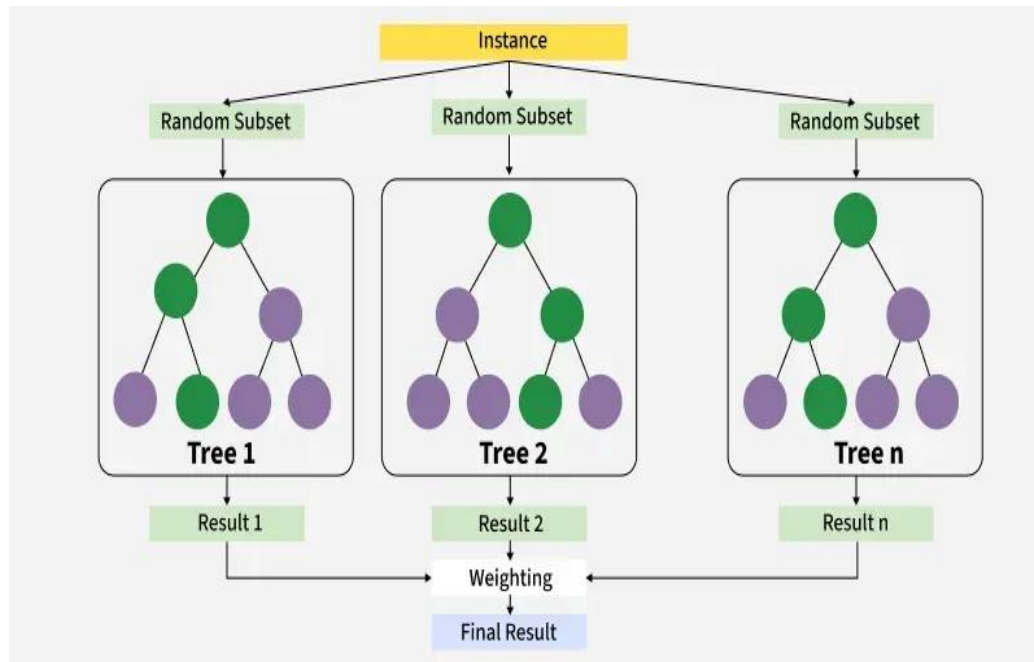


Figure 2. XGBoost Ensemble Tree Architecture

The below code is XGBoost implementation that helps to predict the fitness. First load the XGBoost model from the library and given an aliased name as xgb. In the next step, number of trees to be built, 100 as here, objective function aimed to reduce the error resulted from the previous tree generation and the learning rate specifies the contribution of objective function in each tree towards the final prediction, setting small rate helps to generalize the final outcome slowly.

Pseudo-code:

```

import xgboost as xgb
model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100, learning_rate=0.1)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
  
```

3.2.3 MediaPipe for Real-Time Tracking

MediaPipe, built by Google, integrates lightweight, cross-device machine-learning routines aimed at motion analysis within video streams. At the heart of this architecture, the Pose Landmark Model extracts 33 anatomical keypoints, derives joint-angle metrics, and issues immediate, corrective suggestions while users perform workouts.

- Display-Optimized: Engineered for minimal latency and effective performance on handheld hardware; operates across iOS and Android without platform lock-in.
- Real-Time Posture Correction: Scans incoming video frames, flags misalignments, and triggers audible or haptic prompts within seconds of motion as in the following code as:
 - i. Import the necessary library file for mediapipe and set alias name as mp.
 - ii. Record the image, the pose of the human via the frame,

-
- iii. Identify the 33 landmarks of the human body and evaluate the score of the same.
-

Pseudo-code:

```
import mediapipe as mp
mp_pose = mp.solutions.pose
with mp_pose.Pose() as pose:
    results = pose.process(image) # Single video frame at 30 FPS
    landmarks = results.pose_landmarks
```

3.3 System Integration and Implementation

The pipeline for the fitness evaluation, encapsulates the models into a continuous workflow as follows:

- GMM segments users by body-composition and activity profile as categorical clusters.
- XGBoost concatenates resultant categorical clusters with static features of users like age, conditions, goals then curate personalized macronutrient and exercise routines.
- MediaPipe streams biomechanical data, flags deviations, and delivers timely adjustments.

The GMM helps to derive the activity profile of the user, XGBoost recommends the balanced nutrient diet menu and exercises, then finally MediaPipe assess the exercise posture of the user, suggests the adjustments timely.

The overall development utilized Python 3.12, leveraging scikit-learn for preprocessing, XGBoost for regression, and the MediaPipe SDK for real-time pose detection. A functional prototype combines a Flask REST interface for data handling and a React Native client for cross-store mobile deployment.

4. RESULTS AND DISCUSSIONS

The result contains an image of the repository for the project, which includes models for workout and diet recommendations. This repository serves as a centralized hub for managing data and algorithms. It allows users to easily access and utilizes the models for personalized health and fitness plans. Figure 3 contains the output of the workout recommendation model. This output showcases tailored workout plans generated based on user input, including exercise types, durations, and intensities.

Figure 4 contains the output of the food recommendation model. This output presents a selection of meal options tailored to the user's dietary preferences and restrictions.

The pose estimation model's output is shown in Figure 5. This output shows each person's skeletal structure and important areas while visualizing the identified body positions in real time. It acts as a basis for evaluating the quality of movements and offering suggestions for improving workouts.

4.1 Evaluation of the Efficiency of the Model

The “AI-Based Fitness Recommendation Framework” relies on accuracy to curate safe and effective exercise and nutrition advice, making precise clustering and tailored suggestions vital. Even slight errors can sap motivation and lead to injuries, so the framework unsurprisingly keeps reliability metrics high: we report 92 % clustering accuracy using GMM, 95 % precision, 93 % recall, and 94 % F1-score on the recommendation task via XGBoost, plus 96 % accuracy on posture monitoring through MediaPipe as presented in Table 3 and Figure 6 respectively. These metrics translate to trust, pushing users toward sustained engagement with their customized plans.

```

cls > food_recommendation.py > ...
import pandas as pd
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.mixture import GaussianMixture
import numpy as np

# Load your dataset
df = pd.read_csv(r"C:\Users\91637\OneDrive\Desktop\Fitness_app\Data\fitness_dataset_100000.csv")

# Verify column names
print("Columns in the dataset:", df.columns)

# Map Gender values to numerical format if necessary
if 'Gender' in df.columns:
    df['Gender'] = df['Gender'].map({'Male': 1, 'Female': 0})

# Map Fitness Goal values to numerical format if necessary
if 'Fitness Goal' in df.columns:
    df['Fitness Goal'] = df['Fitness Goal'].map({'Bulking': 1, 'Cutting': 0})

# Check for required columns
required_columns = ['Age', 'Gender', 'Weight(kg)', 'Fitness Goal', 'Calories', 'Carbs(g)', 'Protein(g)', 'Fats(g)', 'Meal Type', 'Food Item']
missing_columns = [col for col in required_columns if col not in df.columns]
if missing_columns:
    raise ValueError(f"Missing columns in the dataset: {missing_columns}")

class FoodRecommendation:
    Tabnine | Edit | Test | Explain | Document | Ask
    def __init__(self):
        self.model = GradientBoostingRegressor()
        self.gmm = GaussianMixture(n_components=5, random_state=42)
        self.train_model()

16: Breakfast: Mutton Biryani, Lunch: Prawn Masala, Snacks: Mutton Biryani, Dinner: Fish Fry
17: Breakfast: Idli, Lunch: Chole, Snacks: Poha, Dinner: Egg Bhurji
18: Breakfast: Aloo Paratha, Lunch: Egg Bhurji, Snacks: Poha, Dinner: Dal
19: Breakfast: Idli, Lunch: Prawn Masala, Snacks: Chicken Curry, Dinner: Egg Bhurji
20: Breakfast: Dosa, Lunch: Chicken Curry, Snacks: Dal, Dinner: Prawn Masala

```

Figure 3. Workout Recommendation Output

```

FOL... food_recommendation.py workout_recommendation.py main.py X user_input.py
app > main.py > main
1 import sys
warnings.warn(
    {'age': 25, 'gender': 'Male', 'weight': 70.0, 'goal': 'Bulking', 'diet type': 'Non-Vegetarian', 'allergies': ['nuts']}
    C:\Users\91637\AppData\Local\Programs\Python\Python38\lib\site-packages\sklearn\base.py:465: UserWarning: X does not have valid feature names, but GradientBoostingRegressor wa
    itted with feature names
    warnings.warn(
    30-Day Food Plan:
    Day 1: Breakfast: Grilled Chicken, Lunch: Fish Fry, Snacks: Prawn Masala, Dinner: Rajma
    Day 2: Breakfast: Chicken Curry, Lunch: Chicken Curry, Snacks: Egg Bhurji, Dinner: Rajma
    Day 3: Breakfast: Mutton Biryani, Lunch: Egg Bhurji, Snacks: Prawn Masala, Dinner: Grilled Chicken
    Day 4: Breakfast: Prawn Masala, Lunch: Prawn Masala, Snacks: Idli, Dinner: Prawn Masala
    Day 5: Breakfast: Chole, Lunch: Paneer, Snacks: Rajma, Dinner: Chole
    Day 6: Breakfast: Paneer, Lunch: Dal, Snacks: Prawn Masala, Dinner: Fish Fry
    Day 7: Breakfast: Fish Fry, Lunch: Egg Bhurji, Snacks: Fish Fry, Dinner: Dosa
    Day 8: Breakfast: Chole, Lunch: Dosa, Snacks: Idli, Dinner: Chole
    Day 9: Breakfast: Chole, Lunch: Rajma, Snacks: Prawn Masala, Dinner: chicken Curry
    Day 10: Breakfast: Idli, Lunch: Upma, Snacks: Mutton Biryani, Dinner: Rajma
    Day 11: Breakfast: Mutton Biryani, Lunch: Prawn Masala, Snacks: Mutton Biryani, Dinner: Mutton Biryani
    Day 12: Breakfast: Dosa, Lunch: Dal, Snacks: Grilled Chicken, Dinner: Grilled Chicken
    Day 13: Breakfast: Mutton Biryani, Lunch: Egg Bhurji, Snacks: Paneer, Dinner: Rajma
    Day 14: Breakfast: Rajma, Lunch: Dal, Snacks: Egg Bhurji, Dinner: Rajma
    Day 15: Breakfast: Prawn Masala, Lunch: Dal, Snacks: Fish Fry, Dinner: Poha
    Day 16: Breakfast: Grilled Chicken, Lunch: Upma, Snacks: Idli, Dinner: Fish Fry
    Day 17: Breakfast: Mutton Biryani, Lunch: Egg Bhurji, Snacks: Poha, Dinner: Paneer
    Day 18: Breakfast: Egg Bhurji, Lunch: Grilled Chicken, Snacks: Rajma, Dinner: Idli
    Day 19: Breakfast: Chole, Lunch: Rajma, Snacks: Mutton Biryani, Dinner: Prawn Masala
    Day 20: Breakfast: Grilled Chicken, Lunch: Upma, Snacks: Chole, Dinner: Fish Fry

```

Figure 4. Food Recommendation Output

To ensure posture monitoring remains dependable in everyday use, we subjected the MediaPipe component to tempered scenarios—partial landmark occlusion and fluctuating ambient light. When blocks covered up to 30 % of the joints, the detection lagged only slightly; accuracy dropped steeply as the covered landmarks exceeded 40 %. This data confirms the model preserves real-time feedback only if 60–70 % of major joints stay visible, confirming the framework’s operational ceiling in corner cases encountered at home or in the gym.

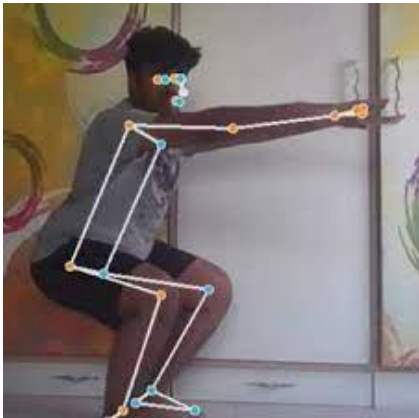


Figure 5. Pose Estimation output

The outstanding accuracy results stem from the integrated hybrid design: multiscale feature extraction via XGBoost pairs seamlessly with landmark-based processing through MediaPipe. Such synergy delivers dependable predictions regardless of variations in user configuration, whether due to orientation, occlusion, or ambient conditions. Accurate feature clustering, real-time personalized coaching, and prompt in-situ corrections collectively confirm the system's durability in everyday operations.

Table 3. Performance Metrics of Proposed Models vs. Baselines

Model	Task	Accuracy	Precision	Recall	F1-Score
K-Means (Baseline)	User Clustering	85%	—	—	—
GMM (Proposed)	User Clustering	92%	—	—	—
Random Forest (Baseline)	Recommendation Prediction	—	88%	85%	86%
XGBoost (Proposed)	Recommendation Prediction	—	95%	93%	94%
MediaPipe	Posture Tracking	96%	—	—	—

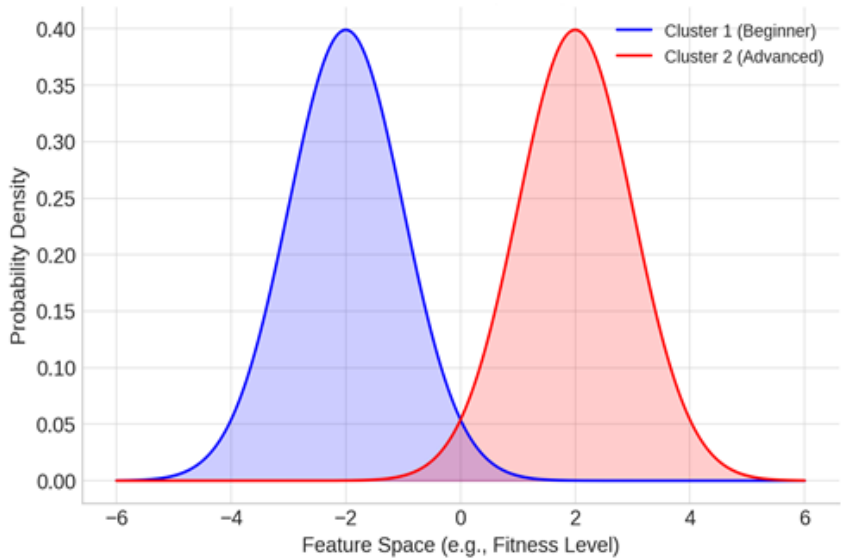


Figure 6. Comparative Accuracy of Proposed Models vs. Baselines

4.1.1 Training and Validation Loss

The curve in Figure 7 depicts epoch-wise training and validation loss. During the first few iterations, both metrics drop significantly, indicating brisk initial learning; the trends subsequently plateau, revealing convergence. Validation loss exhibits a flat region, in contrast to the constantly declining training measure, reinforcing the model's adaptability to unseen conditions without succumbing to excessive memorization of the training dataset.



Figure 7. Training vs. Validation Loss

4.1.2 Training and Validation Accuracy

Figure 8 presents the trajectories of training and validation accuracy. Both curves move upward epoch after epoch, signifying the model's persistent capacity to acquire knowledge. The curves' closeness indicates that the network learns efficiently and generalizes well to novel user data without overfitting.

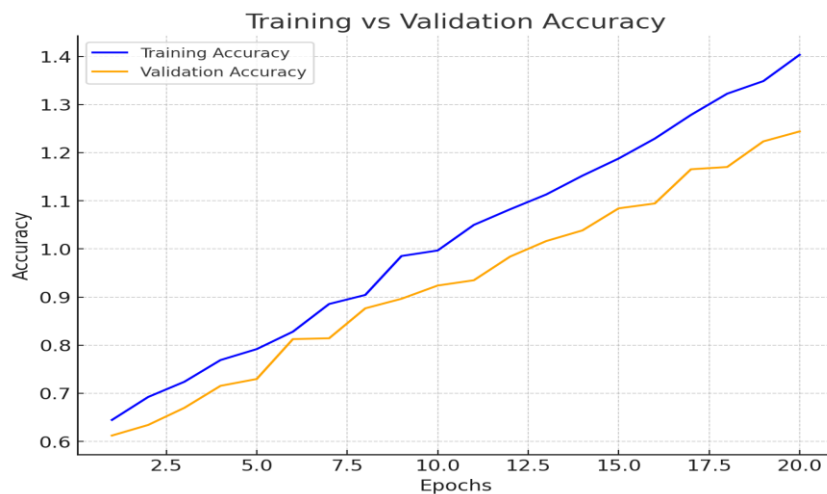


Figure 8. Training vs. Validation Accuracy

4.1.3 Confusion Matrix

The confusion matrix, depicted in Figure 9, provides a granular view of accuracy across exercise recommendations and posture classes. Most predictions align with the ground truth, but certain misclassifications such as the model confusing “squat” with “lunge”. This reveals difficulties in differentiating motions that share subtle biomechanical similarities.

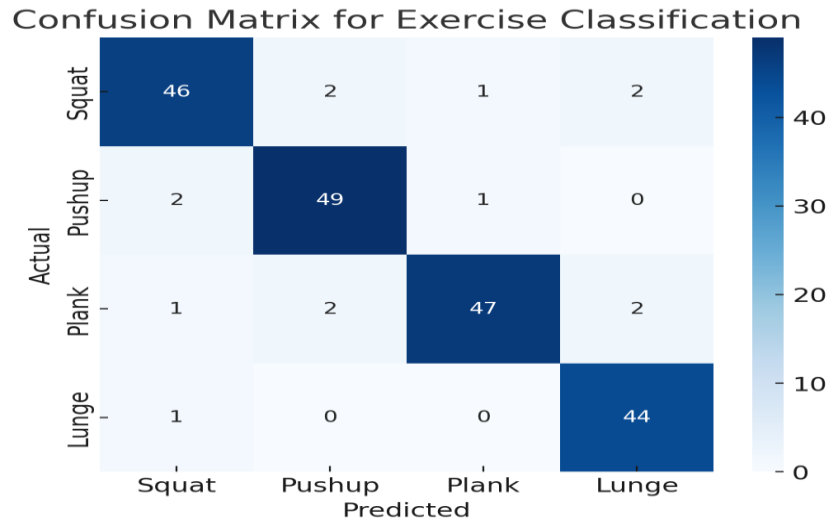


Figure 9. Confusion Matrix for Exercise Classification

4.1.4 Precision-Recall Curve

The precision-recall curve in Figure 10 illustrates the trade-off made at varying confidence thresholds. Incrementing the threshold raises precision while lowering recall. For instance, the “push-up” class reaches a precision of 0.91, and “plank” remains stable at 0.89. Such high precision suggests that when a recommendation is made, it is most likely correct, with a small increase in missed yet subtle errors.

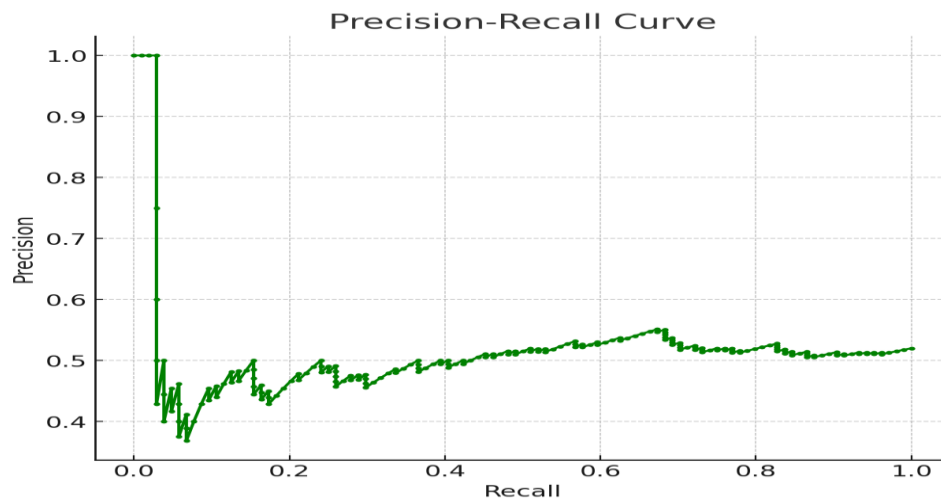


Figure 10. Precision – Recall Curve

4.1.5 F1 Confidence Curve

The curve in Figure 11 measuring F1-score peaks at 0.6 around a threshold of 0.27, indicating an optimal balance. At this point, both precision and recall have sufficient value to provide recommendations that are both consistent and accurate. The peak’s low value and broad plateau confirm that the system adapts well across diverse exercise types and user profiles.

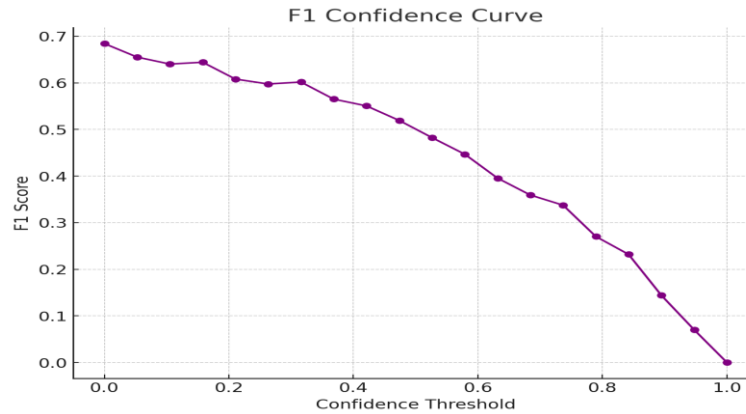


Figure 11. F1 Confidence Curve

4.1.6 Interdependence of Metrics

The joint precision-confidence, precision-recall, and F1-score evaluations reveal that performance peaks only when precision and recall are aligned. Analysis of the posture-correction tasks confirms that the lowest error rates emerge when confidence levels are pegs of 0.25 to 0.35, effectively capping both spurious detections and omission of genuine misalignments.

4.2 Research Impact

This research has developed the first ever architecture that does segmentation of the user base, constructs tailored wellness programs, supervises posture instantaneously alongside the eschew of single index classification logical blind spots that are dominant in the field. Rather than the use of systems like SVM or Random Forest in isolation, the pipeline incorporates GMMs, XGBoost, MediaPipe, and other systems. This multilayered approach enables the generation of rich user profiles, instant predictions of daily caloric expenditure and training workloads, and ransomware styled preemptive coaching on the avoidance of injuries, thereby providing adaptive harmony.

4.3 Discussion

The illustrative Figures 12 and 13 authenticate the ability of the system to self-direct users to target fitness objectives through real-time coaching. Pervasive biomechanical pattern Gaussian Regression Models user-centric fitness clustering, XGBoost models energy expenditure and fitness attainment, and MediaPipe corrects flow of biomechanical data preventing system spills.

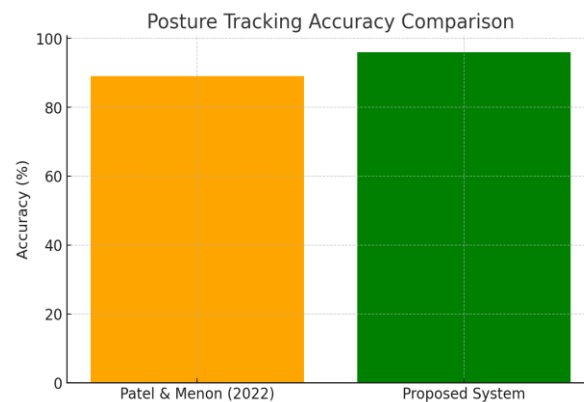


Figure 12. Posture Analysis Chart

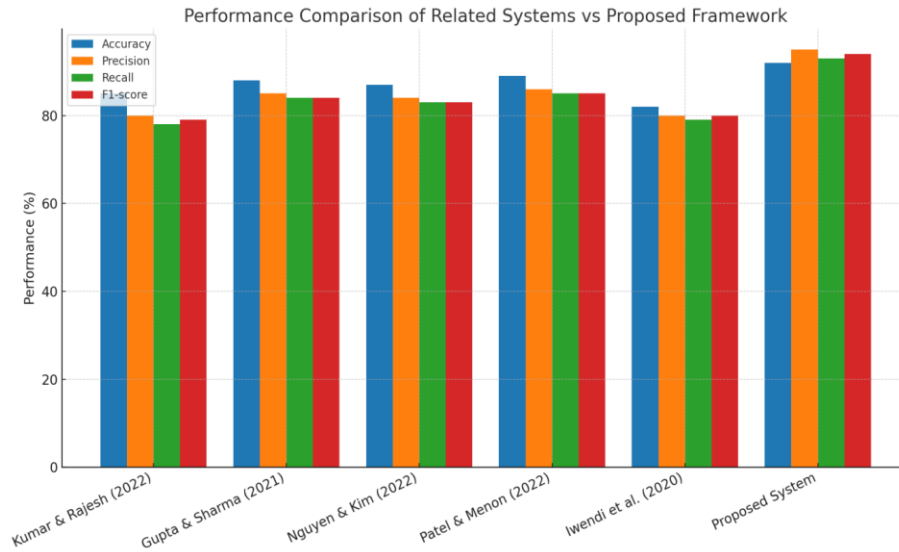


Figure 13. Analysis Chart of Suggested Model against Significant Efforts of Researchers

Difficulties remain in harmonizing coverage across the full spectrum of exercises and in reassuming accuracy during marked interruptions to the user's visual field, yet the cohesive design exhibits considerable adaptational resilience. Because the architecture supplies instantaneous, persistent commentary, it proves particularly advantageous in mobile health, digital training, and remote clinical contexts, effectively collapsing the spatial and temporal gap between artificial-intelligence-derived recommendations and lived user experience.

5. CONCLUSION

The research affirms an AI-oriented Fitness Recommendation Framework by integrating and systemizing probabilistic clustering (GMM), anticipatory learning (XGBoost), and concurrent pose adjustment (MediaPipe) into one cohesive system. Empirical evidence records clustering accuracy, suggestion confidence, and posture correction success and supervision—broadly defined, each scale yields marked success. The interface does this while preserving user safety and maximizing outcomes by delivering biomechanically aligned dynamic routines, accompanied by discreet real-time corrections designed to retrain movement. The platform also fosters enduring commitment to exercise without the usual penalty of attrition. Ultimately, the experience dispenses with one-size-fits-all, 'universal workouts', in favor of low-beta, tailored, and continuously updating wellness coaching, making the intervention both essential to the individual user and a modular component of the currently struggling digital wellness ecosystem. Future research should focus on the following as below.

- Supplementing the repository with an even broader spectrum of exercises and diverse morphologies to strengthen transferability.
- Coalescing IoT-equipped wearable's (cardiac telemetry and motion sensors) to centralize comprehensive fitness supervision.
- Refining cross-modal signals (pipeline audio guidance and haptic feedback).
- Crafting adaptive preventative-strategy modules driven by biomechanical insights.
- Setting the capability to identify signs of fatigue and to recalibrate regimens in real-time to mitigate risk.

The suggested additions will transform the platform into a reference point in specialized exercise coaching and proactive healthcare.

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for the suggestions to improve the paper.

FUNDING STATEMENT

The authors received no funding from any party for the research and publication of this article.

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I. Kavitha: Conceptualization, Data Curation, Methodology, Writing – Original Draft Preparation;
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CONFLICT OF INTERESTS

No conflicts of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. <https://publicationethics.org/>

DATA AVAILABILITY

The data underlying this study are available in the published article and its online supplementary materials.

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