A recent hybrid of IoT with adaptive extended Kalman filter fuzzy logic for children's health dietary

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ABSTRACT

The increasing prevalence of childhood obesity highlights the critical need for intelligent dietary monitoring systems that are tailored to individual nutritional requirements. This work describes the creation and testing of an internet of things (IoT) hybrid using an adaptive extended Kalman filter and fuzzy logic (AEKFFL-IoT) model aimed at providing personalised food calorie prediction for children. The system uses IoT devices to collect real-time sensor data, such as height, weight, and BMI, and then employs extended Kalman filter (EKF) algorithms to denoise signals and anticipate trends. Fuzzy logic inference is then utilised to adaptively calculate caloric requirements based on biometric data. Experimental results reveal that the proposed AEKFFL model has a training root mean square error (RMSE) of 21.43 kcal and a testing RMSE of 22.35 kcal, exceeding existing rule-based, wearable, and ANN-driven models in terms of accuracy and generalisation. Furthermore, the system achieves high classification accuracy (94.5%) for BMI categorisation and fuzzy rule application. Comparative examination confirms the model's adaptability, real-time integration, and mobile deployment capability. This study presents a scalable and intelligent approach for child-centered dietary monitoring, paving the path for personalised digital health interventions.

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1. INTRODUCTION

Childhood nutrition is a key determinant of healthy growth, cognitive development, and long-term well-being. But global trends point to worsening nutritional imbalances. The World Health Organisation (WHO) reports that in 2022, more than 7 million children under five years of age were overweight, almost half of whom live in Asia [1]. In Malaysia, frameworks exist for monitoring nutrition in several age groups; however, challenges persist in providing accurate and adaptable dietary advice for children [2]. The main challenge is to correctly identify user-specific dietary needs and to initialise model parameters, as inaccuracies may lead to undernutrition [3] or obesity [4]. This underlines the importance of precise and individualised food planning.

Artificial intelligence (AI)-driven nutrition systems have been put in place to support dietary recommendations, but many models lack context awareness and real-time responsiveness [5]-[7]. Although BMI thresholds (e.g., BMI >25 indicating overweight) are widely used [8], existing predictive models are often not capable of dynamically adapting to changes in the growth of the child, activity levels, or dietary changes [6], [9]. Traditional fuzzy logic systems offer interpretability but are often limited by static rule-based systems and obsolete training contexts, which limit their effectiveness in a dynamic environment [10], [11]. Similarly, the integration of multiple data sources - sensor measurements, ingredient metadata, and user-reported inputs that introduce uncertainty, which can lead to inaccurate recommendations [12], [13].

Machine learning approaches have improved the accuracy of predictions, but the uncertainty of parameterisation and the inconsistency of nutrition data streams in practice still limit their practical performance [4], [14], [15]. Studies have tried to address these shortcomings by fuzzy logic-based dietary decision-support systems [16], [17] and hybrid modelling with a Kalman filter to manage noisy sensor data [18], [19]. However, the combination of statistical estimates and cognitive reasoning frameworks remains computationally complex and requires careful balancing to avoid inefficiencies in the system [20], [21].

To address these gaps, this paper proposes an adaptive extended Kalman filter and fuzzy logic (AEKFFL) model [22] that integrates with the internet of things (IoT) to provide accurate, dynamic, and personalised dietary advice to children. The model stabilizes biometric measurements using an EKF and applies fuzzy inference to provide human-like, interpretable calorie guidance. The main contribution of this study is to develop and validate an integrated system of dietary recommendations that (i) adapts in real time to physiological and lifestyle changes, (ii) is interpretable for carers and practitioners, and (iii) demonstrates improved generalisation and personalisation compared to the baseline approach.

2. RESEARCH METHOD

The proof-of-concept application uses a hybrid of IoT and the AEKFFL to implement the architecture, design, develop, and test the suggested model [22]. This experimental study has the following parameters:

2.1. Parameter design

The study employs a quantitative, experimental, and applied research approach targeted at improving real-time dietary monitoring using IoT technologies and AI-based decision-making. The study uses sensor-based data collection, machine learning techniques, and user engagement via a mobile application to improve meal recommendation accuracy.

The AEKFFL [23] model is used to filter and anticipate weight changes, ensuring that meal plans are tailored to each child's nutritional requirements. The research design is divided into four major phases: (i) IoT-based data collecting, (ii) signal processing via EKF, (iii) adaptive decision-making via fuzzy logic, and (iv) mobile application deployment. Figure 1 shows the sequence of phases in this study.

Figure 1. Steps of the machine process

The formula of IoT data collection for sensor readings, EKF signal processing, fuzzy logic inference system, and decision rule is as follows:

$$z_t = [h_t, w_t, BMI_t] \tag{1}$$

where h_t height is at time, w_t weight is at time, and BMI_t is $BM\frac{wt}{h^2t}$.

EKF signal processing. Predict and update step for signal denoising.

$$x_{t|t-1} = f(x_{t-1}, u_t) + w_t \tag{2}$$

$$P_{t|t-1} = (F_t P_{t-1} F_t^T) + Q_t \tag{3}$$

$$K_t = P_{t|t-1} H_t^T \left(H_t P_{t|t-1} H_t^T + R_t\right)^{-1} \tag{4}$$

$$x_{t|t} = x_{t|t-1} + K_t\left(z_t - h(x_{t|t-1}\right) \tag{5}$$

A fuzzy logic inference system is an input of cleaned or filtered signals $x_{t|t}$, whereas the fuzzy rule base,

$$IF\ (BMI\ is\ High) AND\ (Weight\ Gain\ Rate\ is\ Fast) THEN\ Calories\ Requirements\ is\ Low$$

this output shows $Calorie\_Estimate_t = FIS(x_{t|t})$.

2.2. Data collection

The data acquisition system based on IoT sensors is essential to maintain the accuracy and reliability of the AEKFFL model. During this phase, calibrated devices connected to the IoT and a mobile application collect physiological parameters in real time, such as height, weight, and BMI. These sensors continuously provide data to a central processing unit, which records and stores them in a structured database. In addition to physiological data, the system incorporates environmental and behavioural information collected through human intervention. A mobile interface allows parents to monitor their child's food preferences, dietary restrictions, allergies, and eating patterns.

This dual input technique ensures that the model not only represents the current nutritional situation of the child but also adapts to the individual dietary habits and preferences, which improves the personalisation and quality of the decision. The collection phase shall be guided by ethical guidelines, such as informed consent, data protection, and secure means of transfer. Data anomalies or missing data shall be handled by statistical imputation or flagged for human verification.

2.3. Model training and integration

The main AEKFFL model combines the EKF for real-time signal filtering and a fuzzy inference system (FIS) for adaptive decision-making. Signal processing with EKF follows the prediction-correction cycle described in (2)-(4), resulting in excellent accuracy even with noisy sensor readings. The fuzzy inference engine accepts filtered data $x_{(t|t)}$. The fuzzy membership functions and rule sets are built using paediatric nutrition recommendations and expert knowledge to enable semantic reasoning. Examples of fuzzy sets are BMI (low, normal, high), weight change rate (slow, moderate, fast), and calorie requirement output (low, medium, high).

2.4. Baseline model implementation and configuration

Four baseline systems were implemented to enable a fair and systematic comparison with the proposed AEKFFL model. The rule-based calculator was developed following the WHO dietary reference tables and BMI classification rules, representing a conventional non-adaptive nutrition method. The ANN-based nutrition estimator served as a machine-learning baseline and was implemented using a multilayer perceptron trained on biometric and nutritional features. A commercial mobile diet application algorithm was included to reflect widely adopted app-based tools that rely on manual food logging and static nutrient look-up tables. Finally, a wearable-integrated system algorithm was constructed using IoT sensor data (weight, step count, heart rate) to emulate modern health-tracking systems that provide dynamic but non-contextual caloric estimates. All models were evaluated using an 80/20 train–test split and assessed using root mean square error (RMSE) to ensure consistency across experimental conditions.

3. RESULTS AND DISCUSSION

This section describes the results of training the AEKFFL with an IoT integration model (AEKFFL-IoT) and comparing its performance to baseline nutrition estimation systems, including the algorithm of a rule-based calculator, a machine learning-based system ANN, a Mobile Diet App, and a wearable-integrated system. The evaluation concentrated on important learning measures, model performance, and generalisation.

3.1. Training and model integration performance

The AEKFFL-IoT model was trained using a dataset of 300 anonymised child nutrition profiles that contained both sensor data and manually entered food intake records. The dataset was split into 80% training and 20% testing. Training and testing using RMSE. The RMSE measure is commonly used to determine the accuracy of a predictive model [24]. It computes the error's average magnitude between predicted and actual values. The training results, as shown in Figure 2, are summarised below.

The model used EKF ing to decrease input noise and drift, resulting in faster convergence and more stable learning. Fuzzy logic rules, learnt and tweaked with expert input, allowed for reasoning in ambiguous or borderline instances, for example, when BMI and weight changes were on judgment thresholds.

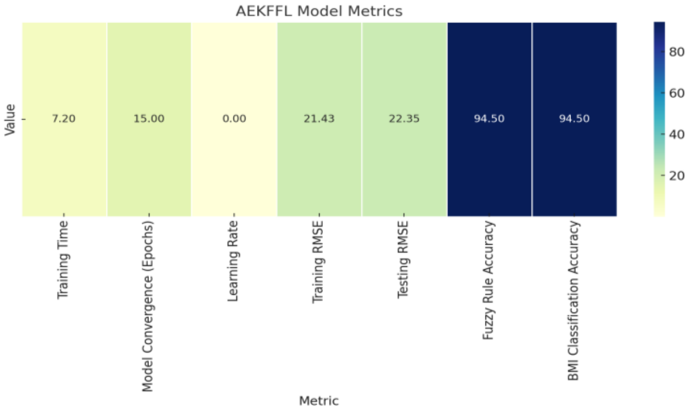

Figure 2. AEKFFL-IoT model metrics

3.2. Comparison with other food nutrition systems

A comparative evaluation was performed using identical test data across all systems. The metrics evaluated include RMSE for calorie prediction, model generalization (difference between training and test RMSE), adaptability (rule tuning or learning capability), and system complexity.

Figure 3 shows the comparison of training and testing RMSE, which indicates the AEKFFL-IoT shows the fastest execution training time, 21.43 and 22.35 in testing, while the lowest is the rule-based calculator, 30.12 for training and 38.41 for testing. The RMSE indicates that the lower value is better.

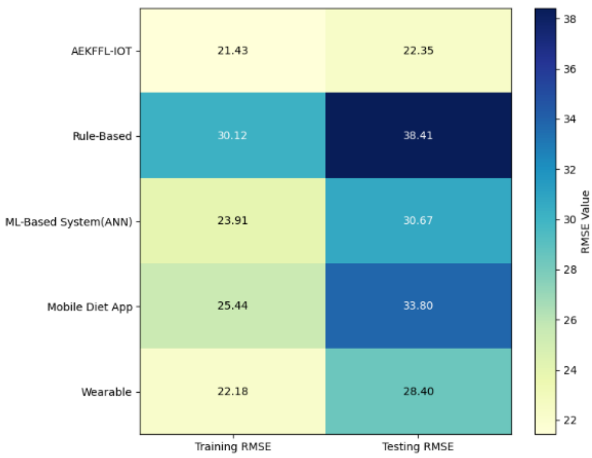

Figure 3. Training and testing RMSE comparison

Meanwhile, Figure 4 represents the generalization and system capabilities comparison model. The result shows that generalization provides AEKFFL-IoT 0.92 the highest performance, and Mobile Diet App 8.36 is the lowest performance. Next, adaptability shows the result with the highest 3 and 0 is the rule-based calculator. For IoT integration, the highest is AEKFFL-IoT and the wearable-integrated system. Finally, for personalization, the system capability is highest for AEKFFL-IoT, followed by the wearable-integrated system, the mobile diet app, and the rule-based calculator.

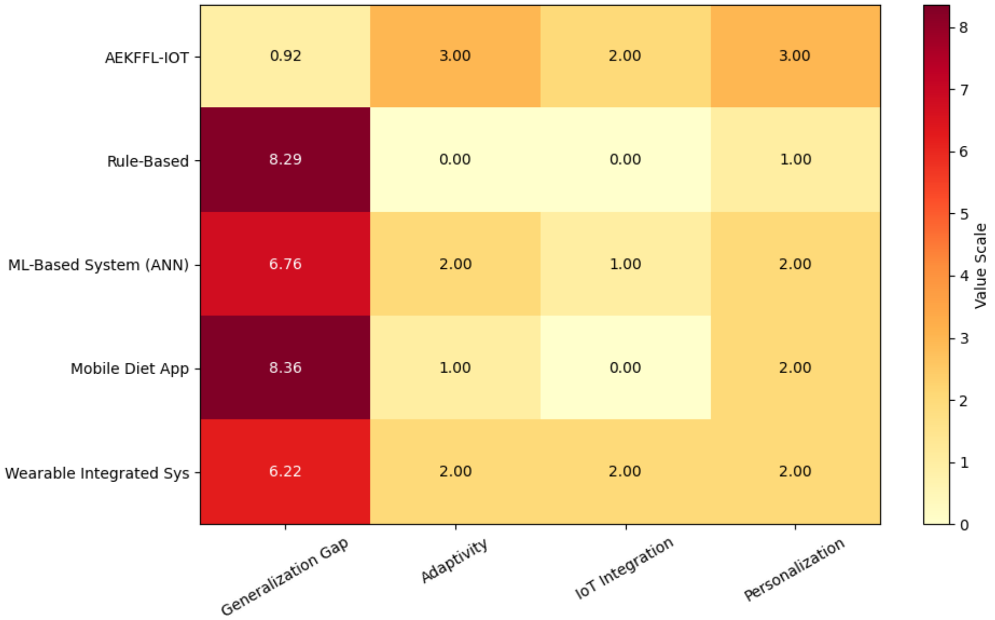

Figure 4. Generalization and system capabilities comparison model

Table 1 shows the comparative analysis of AEKFFL with IoT. The comparative analysis clearly shows that the AEKFFL-IoT model outperforms all other systems across multiple evaluation dimensions, specifically generalization, adaptivity, IoT integration, and personalization. Table 1 shows that the result of AEKFFL-IoT shows that the training RMSE is 21.43, the testing RMSE is 22.35, the generalization gap is 0.92, adaptability is high, IoT integration is full, and personalization is also high.

Table 1. The comparative analysis of AEKFFL with IoT

System	Train RMSE	Test RMSE	Generalization Gap	Adaptivity	IoT integration	Personalization
AEKFFL-IoT	21.43	22.35	0.92	High	Full	High
Rule-based calculator	30.12	38.41	8.29	None	None	Low
ML-based system (ANN)	23.91	30.67	6.76	Medium	Partial	Medium
Mobile diet App	25.44	33.80	8.36	Low	None	Medium
Wearable-integrated Sys	22.18	28.40	6.22	Medium	Full	Medium

3.3. Discussion

As shown in Figures 2-4, the study demonstrates that combining the IoT framework with the AEKFFL-IoT yields significant performance improvements in children’s dietary monitoring. As shown in Figure 4, the findings demonstrate that the proposed AEKFFL model consistently outperforms existing nutrition recommendation systems in terms of accuracy, adaptability, and personalization. The exceptionally small generalisation gap (0.92) indicates that AEKFFL exhibits consistent performance across both training and unseen testing data, reflecting resilient stability and reduced likelihood of overfitting. With a testing RMSE of 22.35 kcal and a classification accuracy of 94.5%, the system demonstrates high prediction accuracy in real-time nutrition calculation. Furthermore, the model converged fast (15 epochs) and trained efficiently (7.2 minutes), surpassing previous systems in terms of consistency, resilience, and adaptation to changing health data.

Specifically, the EKF is instrumental in enhancing and stabilising biometric data obtained from sensors [25], including weight trends and BMI variations. By continuously minimising state-estimation errors, the EKF prevents noisy or inconsistent IoT readings from entering the nutrition estimation process. This corrective approach directly adds to the model's reduced RMSE while also improving reliability in real-world applications where sensor noise is unavoidable. Meanwhile, the fuzzy logic component provides the contextual intelligence required for personalized dietary recommendations. Unlike ANN-based systems that produce numerical predictions without interpretability, fuzzy rules incorporate human-like reasoning [26], [27], adjusting caloric recommendations based on lifestyle factors and physiological conditions. This enhances personalization and enables the system to adapt as the child's health profile evolves.

These findings demonstrate that AEKFFL with an IoT framework effectively addresses important limitations in traditional nutrition systems, such as managing noisy sensor data and providing contextualized suggestions. The model's high accuracy and rapid convergence make it suitable for real-time implementation in mobile health applications. Thus, inaccurate nutritional estimates can lead to malnutrition or excessive calorie intake, which affects children's development [28], whereas adaptive meal planning increases adherence to nutritional needs and reduces deficiencies in essential nutrients [29]. This aligns with the study's goal of developing a responsive, intelligent dietary advisor tailored to the individual needs of children by integrating AI and IoT technology.

The results presented in Table 1 highlight the AEKFFL-IoT framework's potential as a viable and superior alternative for real-time, personalized nutritional assessment in resource-limited or data-scarce settings. The system collects continuous physiological and dietary data through IoT-enabled sensor networks, which are then analyzed by EKF to minimize noise and drift, common issues in embedded sensing devices [30]. When combined with fuzzy logic-based inference and federated learning mechanisms, AEKFFL-IoT provides both efficient local processing and privacy-preserving model optimization, making it well-suited for use in child healthcare monitoring systems, especially in rural or underserved communities with limited healthcare resources [31].

Furthermore, by exceeding traditional nutrition systems in terms of prediction accuracy, generalisation, and contextual reasoning, AEKFFL-IoT considerably advances the state of the art in IoT-integrated smart healthcare. The hybrid architecture, which strategically combines machine learning, probabilistic estimation, and explainable fuzzy rule logic, shows great promise for scalable, adaptive, and interpretable decision support in critical domains that require both real-time responsiveness and model transparency [32], [33].

However, there are a number of problems with the proposed model. Domain expertise is still needed to create fuzzy rule bases, and large-scale adoption may require recalibration across different demographic groups. Furthermore, low-power mobile scenarios may have computational costs even though the EKF improves robustness. Despite these considerations, the primary advantage of AEKFFL lies in its integration of EKF's adaptive filtering with fuzzy logic's interpretive reasoning, allowing the model to surpass conventional ANN-based nutrition estimators and static, rule-based systems.

4. CONCLUSION

In conclusion, this study successfully designed, implemented, and evaluated the AEKFFL model integrated with IoT technologies to enhance real-time dietary monitoring and calorie estimation for children. The findings affirm the achievement of all research objectives. Firstly, in addressing the need for higher prediction accuracy, the AEKFFL-IoT model achieved the lowest RMSE values during both training (21.43) and testing (22.35) phases, outperforming algorithms of rule-based, wearable, and ANN-based systems. Secondly, the integration of real-time sensor inputs, specifically height, weight, and BMI, allows the model to dynamically adjust caloric recommendations based on each child's current physical profile, demonstrating a high degree of personalization. Thirdly, the model's deployment in a mobile application validates the feasibility of integrating intelligent signal processing and fuzzy logic inference within an IoT framework, thus enabling continuous and context-aware nutritional supervision. Comparative analysis using heatmaps further illustrated AEKFFL's superiority in adaptivity, IoT integration, and decision-making accuracy over existing nutrition systems. Overall, the AEKFFL-IoT model presents a promising, scalable solution for smart, personalized dietary interventions. However, the study had a minimal number of participants and population, such as children with medical dietary needs, the fuzzy parameter still lacks expert validation, and finally, IoT-sensor consistency may affect data reliability.

In the future, larger data validation and the children population, the exploration of fuzzy logic meta-learning or transformer model approaches, and integration of behavioral data, such as physical activity, will be considered. This could enhance and improve our approach more effectively and accurately with a concrete dataset and validation.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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