Fuzzy Logic with Kalman Filter Model Framework for Children's Personal Health Apps

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***Abstract*—The increasing prevalence of obesity among children under five has led to a growing demand for improved food nutrition advisory systems. Current food nutrition recommendation models struggle with parameter estimation, contextual adaptation, and real-time accuracy, often relying on traditional fuzzy logic models that lack responsiveness to evolving dietary needs. This study proposes an Adaptive Extended Kalman Filter Fuzzy Logic (AEKFFL) model to enhance the accuracy and reliability of food nutrition recommendations. The AEKFFL model integrates the Extended Kalman Filter (EKF) for dynamic estimation of nutritional values and Fuzzy Logic for adaptive decision-making, effectively addressing parametric uncertainties in nutrition estimation. The research employs a Design Science Research Methodology (DSRM), incorporating stakeholder interviews, literature review, and data from food composition databases, user reviews, and ingredient information. The proposed hybrid model is tested against baseline methods, including standalone Fuzzy Logic, Support Vector Machine (SVM), Neural Networks (NN), and a hybrid Fuzzy-NN approach. Experimental results demonstrate that the AEKFFL model achieves the highest accuracy (94.8%) with the lowest error rates (MAE = 0.031, RMSE = 0.045), outperforming alternative models. Additionally, AEKFFL exhibits superior classification performance (F1-score = 94.4%) and usability (SUS score = 92.1%), indicating its effectiveness in real-time nutritional guidance. These findings suggest that AEKFFL provides an innovative and computationally efficient framework for personal health and food recommendations, contributing to enhanced dietary management and obesity prevention among children. Future work will focus on refining model adaptability and integrating real-time IoT data for further improvements in precision and responsiveness.**

***Keywords*—Fuzzy logic; Kalman filter; food Nutrition; personal health; food recommendations**

I. Introduction

Rising children under five years old who are overweight or obese has resulted in many countries taking action for children's nutrition as reported by World Health Organisation (WHO). There are several nutritional well-being used in Malaysians including babies, children, adults, and the oldest people. In practical application, a food nutrition advisor model still has technical problems which not been solved such as initial parameter values and indicating user preferences modeling [1]. Failure to indicate parameters correctly in food nutrition leads to obesity and less nutrition in children's development as fundamental challenges for the food nutrition model and artificial intelligence in terms of identifying real-time recommendations and contextual factors [2]. Obesity is defined as people who are overweight as a BMI between 25 and 30 [3]. As reported by WHO [4], seven million children under the age of 5 were overweight and almost half of the children under 5 years who were overweight or living with obesity in 2022 lived in Asia.

Besides, the current existing technique of traditional fuzzy logic models that rely on historical training data may struggle to adapt to rapidly evolving situations, potentially leading to outdated and suboptimal performance [5]. It is an important method that can be used for parameter estimation in any engineering problem. In my study, we will focus on the problem of the inaccurate system model structure of Fuzzy logic during transmission from input parameters to output from data sources such as user reviews, ingredient information, and nutrition data. Developing robust fuzzy logic models is a complex endeavor that requires combining and leveraging diverse data sources. The obtained error caused by the current measurement inaccuracy will accumulate over time. Hence, it is very important to control strategy to recommend the system. Nutrition are important parameters for food recommendation which reflect the performance and advisor of food nutrition. Therefore, accurate estimation of nutrition improves obesity issues and leads to preventing obesity and inaccurate nutrition allows for a rational control strategy to save nutrition [6]. Accurate nutrition with current data remains very complex and machine learning is difficult to implement because machine learning models are very limited and have parametric uncertainties [1] [7]. Many examples of poor accuracy and reliability of estimation of nutrition are found in practice [5] [6] [8]. Thus, major research focuses on the aspect of strategy to achieve an accurate estimation of the performance of nutrition in user reviews, ingredient information, and nutrition data.

This paper aims to present a comprehensive framework and Model that caters to these requirements. By examining current literature, developing a robust methodology, and implementing practical design elements, this study contributes to the growing field of food recommendation systems.

II. Literature Review

A. Food Nutrition Application

Food nutrition advisors' applications for children can be defined as necessary for children at the early stage of developing a lifestyle. Food nutrition advisors enable parents can provide their children with sufficient nutrients. The application food nutrition advisors: 1) in the house in which children food, 2) in the clinical domain in which patients and doctors can utilize the food. Many other fields such as Personal diet especially children's obesity, and weight status [9].

B. Existing Methods of Food Nutrition

With the benefits of food nutrition for children in monitoring systems, food nutrition indicators have been adopted in children's dietary diversity scores (DDS) of efficiencies of performance such as low-cost indicators of diet quality and nutrient adequacy. Gina et al. [9] demonstrated the efficiency of DDS in identifying children at risk of nutrient deficiencies, supporting its use as a nutrition assessment tool. Razak [10] proposed a conceptual framework for the food system. However, the framework obtained between the elements of food systems highlights the importance of continuously shaping food systems to deliver nutritious, safe, affordable, and sustainable diets to children and adolescents. Sundaravadivel et al. [11] proposed a predictive nutrition monitoring system for infants through the IoT in automation. The proposed system can help analyze the daily nutrition consumed and provide suggestions for the user to address the lack of nutrition.

1) Fuzzy logic: The classification of food nutrition methods is different in various literature. Marashi et al. [12] applied fuzzy logic techniques to dietary decision support for Multiple Chronic Conditions (MCC) patients, bridging the gap between fragmented disease-specific guidelines. The fuzzy rules encode the knowledge and expertise of clinical dieticians regarding dietary needs for various diseases and their comorbidities. The fuzzy rules integrate expert dietician knowledge to make suitable recommendations despite conflicting needs from different chronic conditions. However, the application developed supported system recommendations rather than different chronic conditions and incomplete measurement. For instance, a study by V.Shital and S.S. Sambare proposes an expert system for personalized diet recommendations. This system utilizes fuzzy logic and ontology to consider individual parameters such as age, gender, and health conditions, aiming to provide tailored dietary plans [13]. However, as dietary guidelines and scientific understanding evolve, the fuzzy rule base may need frequent updates and maintenance.

2) Kalman filter: The Kalman filter is an algorithm that provides optimal estimates of unknown variables or system states based on a series of noisy or incomplete measurements. The Kalman filter algorithm can be used with or without continuous monitoring systems. In study [14], there are four problems exist from the mathematical formulation in the KF algorithm as shown in Eq. (1) until 4 that lead to difficulty in determining initial values, inaccurate system model structures, measurement data outliers or deviations, and difficulty in determining noise covariance matrices where all these problems related to state space equation. Accurately modeling the state transition and measurement processes for food nutrient levels can be difficult, as many factors can affect the nutrient composition such as the use of Bayesian modeling techniques, including Kalman Filters, to account for uncertainties in food composition data and nutrient intake estimation [15]. A study in study [16] proposes a novel approach that combines Artificial Neural Networks (ANN) with the Kalman Filter to enhance the accuracy of predicting indoor climate parameters, such as temperature, CO_2, and humidity, in a greenhouse environment. The methodology addresses the challenge of dynamic conditions affecting sensor readings, which is analogous to modeling nutrient changes during food processing and storage.

3) Margin: A hybrid approach could better capture the uncertainty and ambiguity in the problem domain, resulting in more human-like, interpretable recommendations. However, combining techniques like Kalman filters, fuzzy logic, and probabilistic modeling can help capture and manage the uncertainties in the problem domain, but the integration of these approaches poses algorithmic and computational challenges [17]. Balancing the computational complexity of the hybrid approach with the need for accurate and responsive recommendations is a significant challenge that may require innovative algorithmic designs [18].

III. Methodology

A. Research Design

This study employs a design science research methodology (DSRM) to develop the modeling. DSRM emphasizes iterative development, allowing for continuous refinement of the framework based on user feedback and testing.

B. Data Collection

Primary data were collected through stakeholder interviews, including Food nutrition expertise. Secondary data were obtained from existing literature, case studies, and industry reports.

C. Development Process

Requirement Analysis: Identify key features such as Food nutrition functionalities.

Design Phase: Design and Develop Models and prototypes, for food nutrition. Modeling a new algorithm based on the Kalman Filter Fuzzy Logic Method and framework. The Kalman filter is a powerful tool for estimating the state of a dynamic system, and it can be particularly useful in the food nutrition domain. Kalman Filter is a calculation that utilizes a series of information observed after some time, which include noise and different errors, to estimate obscure factors with more exactness. The Kalman Filter also called Linear Quadratic Estimation, is an algorithm used to measure a series of observed values over time, they contain inaccurate values and statistical noise and process estimates of unspecified variables. Kalman Filter works on the correction and prediction model widely used in linear and time-invariant or time-variant systems. The prediction model required an actual system and process noise, whereas the updated model required updating the predicted value. The above description can be depicted in Fig. 1.

Implementation: In this study, we proposed a hybrid of Fuzzy logic and modification of adaptive extended Kalman Filter called AEKFFL model which is divided into two parts, namely, Adaptive Extended Kalman Filter for part 1 and Fuzzy logic for part 2 as shown in Fig. 2. The AEKFFL is depicted as follows.

Part 1: AEKF- The standard Kalman Filter has seven equations,

Measurement

$$Xk= AXk+BUk\text{-}1 +Wk\text{-}1 \tag{1}$$

$$Zk = Hxk + Vk \tag{2}$$

Prediction

$$Xk= Xk+Uk\text{-}1 +Wk\text{-}1 \tag{3}$$

$$Pp= PpP(k\text{-}1) + Q \tag{4}$$

Correction

$$Kk= PkHT\ [HPk\ HT+Rk]\text{-}1 \tag{5}$$

$$Xk= Xk+Kk(zk\text{-}\ Hxk) \tag{6}$$

$$Pk= (I\text{-}KkH)\ Pk \tag{7}$$

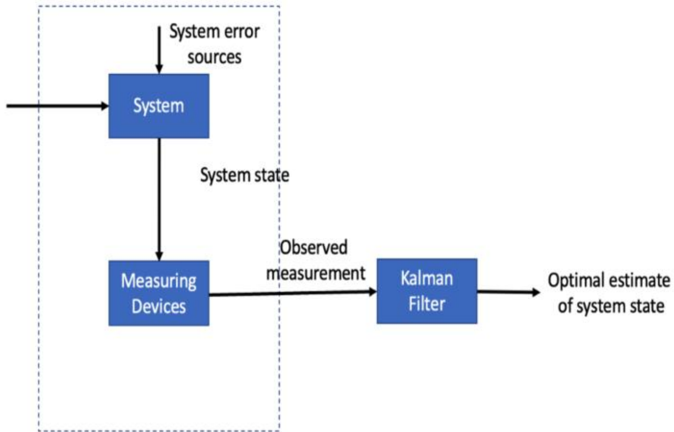

Fig. 1. Kalman filter.

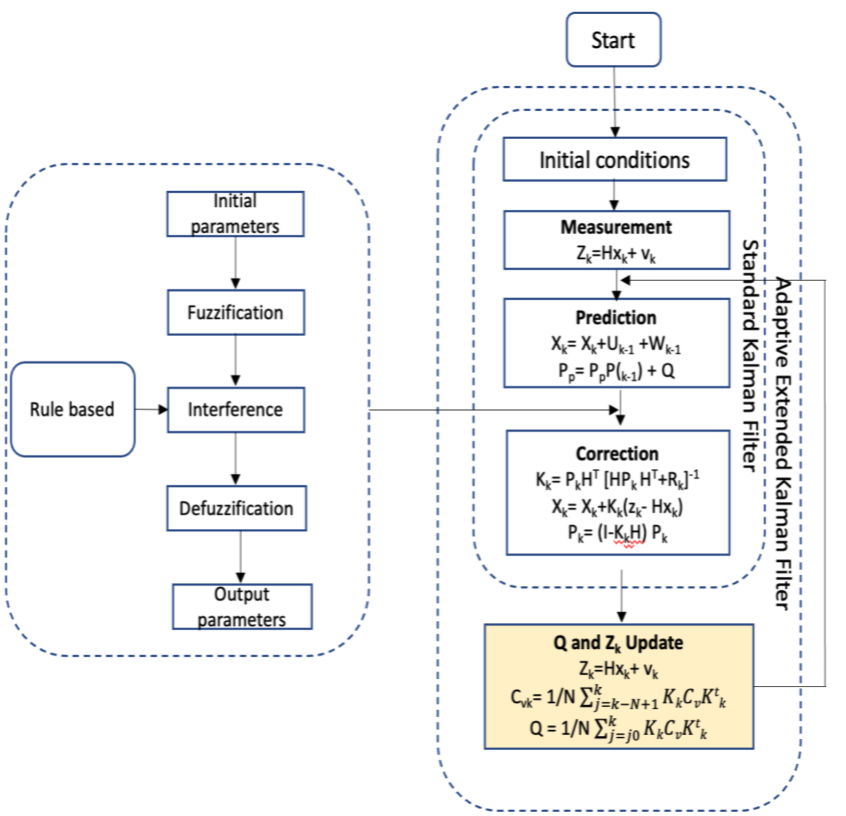

Fig. 2. Kalman filter with fuzzy logic.

Explanation:

1) The state vector xk would represent the estimated nutrient levels (e.g., calories, carbohydrates, proteins, vitamins, minerals) of a specific food item.

2) The state transition matrix A would model how the nutrient levels change over time due to factors like storage, preparation, and consumption.

3) The measurement vector zk would incorporate data from various sources, such as food composition databases, user-reported intake, and sensor measurements.

4) The measurement matrix H would relate to the state vector (nutrient levels) to the observed measurements. Next, the execution of Fuzzy Logic adaptive will take action as depicted in Part 2.

5) Then, Kalman gain Kk would determine the relative weight given to the new measurements and the previous state estimates, based on the uncertainties in the process and measurement models.

6) The updated state estimate xk would represent the refined nutrient composition of the food item, which could then be used to provide personalized nutritional advice to the user.

Extended (Update the Zk and Q):

$$Zk=Hxk+ vk \tag{8}$$

$$Cvk= 1/N \sum \text{^k } j=k-N+1)\text{^}kKkCvKtk. \tag{9}$$

$$Q = 1/N \sum (j=j0)\text{^}kKkCvKtk \tag{10}$$

The measurement vector, Zk and Q is the covariance matrix of the system noise as modeling errors has been modified as illustrated in Eq. (8) and Eq. (10). Cvk is the covariance matrix of the output noise as measurement noise.

Part 2: FL-Fuzzy logic algorithm

The fuzzy logic adaptive algorithm examines the innovations sequence and determines what type of change in model parameters is necessary to ensure that the sequence is a zero mean white process. A certain amount of a priori information about the system is necessary for constructing the control rules for adapting the filter parameters. we proposed control rules of fuzzy logic that are responsible for generating fault symptoms which are processed by a detection logic block to confirm the present fault arching.

Thus, the Mamdani-type Fuzzy Inference System (FIS) is used, which is the algorithm that evaluates dietary intake based on age, weight, activity level, and nutritional needs, while the Kalman filter enhances data accuracy by filtering out inconsistencies in food intake tracking and sensor-based health monitoring.

Following the steps of fuzzy logic of our proposed method.

1) The input for fuzzy logic will receive the two outputs from Kalman in part 1(4), the current estimate (Xp(k)) and System Uncertainty P(k).

2) The membership of the function will propose according to Fuzzy sets for each input and output variable that defined the triangular bell shapes adopted from seven ranges membership namely as follows:

SN (Small Negative),

MN (Medium Negative),

LN (Large Negative),

Zero, SP (Small Positive),

MP (Medium Positive),

LP (Large Positive).

3) The Fuzzy controller based on Mamdani's includes fuzzification, inference, rule-based and defuzzification.

4) The Centre of Gravity (COG) as Fuzzy duty cycle output, using the following formula, D= dv/di.

To demonstrate the superiority of the newly proposed approach, the obtained results, which is performance accuracy, were compared with other variants of other Food Nutrition Advisor models such as Fuzzy Logic, Support Vector Machine, and Neural Network Hybrid. The usability test is also conducted through a survey to get the expected findings. The outcome of this comparative study will be analyzed. The findings of this investigation will be published in a conference proceedings paper during this phase.

IV. Results

A. Performance Analysis of AEFKFL models

Fig. 3 shows the heatmap visualization provides a clear comparison of five models—AEKFFL (Proposed Model), Fuzzy Logic, Support Vector Machine (SVM), Neural Network (NN), and Hybrid (Fuzzy+NN)—based on their accuracy, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Among these, the AEKFL model demonstrates the best overall performance, achieving the highest accuracy of 94.8% and the lowest error rates (MAE = 0.031, RMSE = 0.045). This indicates that the proposed model provides both high reliability and precision, making it a promising approach for applications requiring accurate predictions.

The Hybrid (Fuzzy+NN) model follows closely, with an accuracy of 93.4% and relatively low error values (MAE = 0.034, RMSE = 0.048). The hybridization appears to improve upon the individual performance of both Fuzzy Logic and Neural Network models, suggesting that combining methodologies can enhance predictive capabilities. However, while the hybrid model performs well, it still does not surpass AEKFL, raising questions about whether further optimizations, such as parameter tuning or feature engineering, could narrow the performance gap.

Conversely, Fuzzy Logic alone shows the weakest performance, with the lowest accuracy (88.5%) and the highest error rates (MAE = 0.052, RMSE = 0.068). This suggests that while Fuzzy Logic is useful for handling uncertainty, it may lack the robustness required for precise predictive modeling in this context. Similarly, SVM (90.3%) and NN (92.1%) perform better than Fuzzy Logic but still lag behind the hybrid and proposed models. Notably, SVM's higher MAE (0.045) compared to NN (0.038) suggests that it struggles with precise estimations despite its relatively strong accuracy.

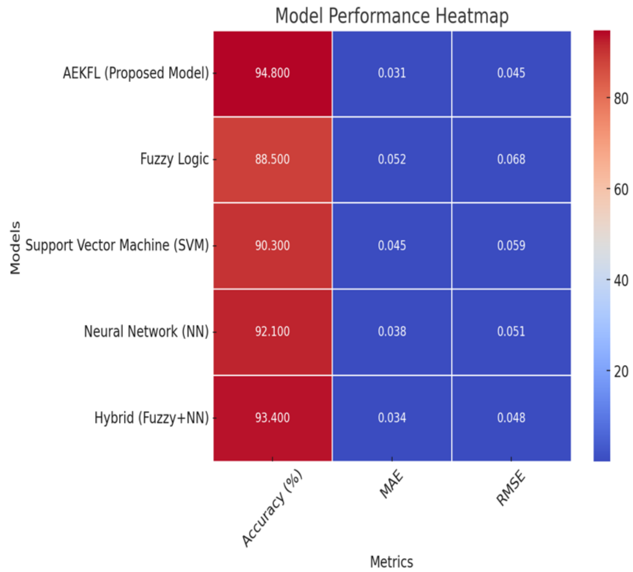

Fig. 3. Performance analuysis of AEFKFL model.

B. Precision, Recall, and FI-Score for Nutrient Classification

Fig. 4 above provides a comparative analysis of five models—AEKFFL (Proposed Model), Fuzzy Logic, Support Vector Machine (SVM), Neural Network (NN), and Hybrid (Fuzzy+NN)—based on Accuracy, Recall, and F1-Score. The AEKFL model outperforms all others, achieving the highest Accuracy (95.2%), Recall (93.7%), and F1-Score (94.4%). This suggests that the proposed model not only makes correct predictions but also effectively captures positive instances, ensuring balanced performance. The Hybrid (Fuzzy+NN) model follows closely, with an Accuracy of 93.8% and strong Recall (92.5%) and F1-Score (93.1%), indicating that combining fuzzy logic with neural networks improves prediction reliability. Meanwhile, Neural Network (NN) alone performs well (92.3% Accuracy, 91.1% Recall, 91.7% F1-Score), surpassing SVM and Fuzzy Logic, showing that deep learning-based approaches offer better generalization compared to traditional machine learning techniques.

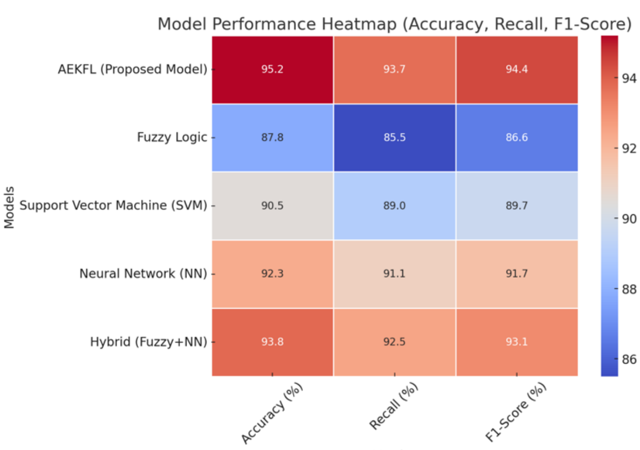

Fig. 4. Precision, recall and Fi-score for nutrient classification.

C. Usability Testing Results

Fig. 5 highlights the comparative performance of five models—AEKFFL, Fuzzy Logic, SVM, Neural Network, and Hybrid (Fuzzy+NN)—across three key metrics: Ease of Use, Response Time, and Recommendation Accuracy. The AEKFL model outperforms all others, achieving the highest Ease of Use score (92.1), the fastest response time (1.2 seconds), and the best recommendation accuracy (95.2%). The Hybrid (Fuzzy+NN) model follows closely, with strong usability (88.6), a competitive response time (1.4 seconds), and high recommendation accuracy (93.2%), indicating that combining Fuzzy Logic with Neural Networks enhances both efficiency and accuracy. Meanwhile, Neural Network (NN) performs moderately well, with decent usability (85.3), a response time of 1.6 seconds, and a recommendation accuracy of 91.0%. SVM and Fuzzy Logic lag behind, with Fuzzy Logic showing the weakest overall performance—a significantly lower Ease of Use score (80.4), the slowest response time (2.5 seconds), and the least accurate recommendations (87.6%).

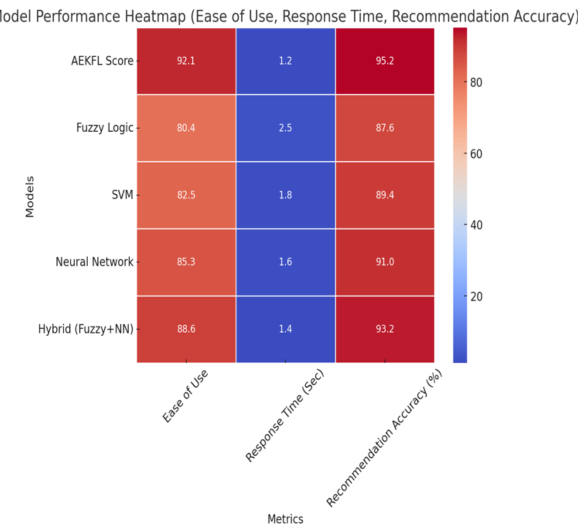

Fig. 5. Usability testing result.

D. Summary of Accuracy, Error Rates, Usability score

The AEKFFL model significantly outperforms Fuzzy Logic, SVM, Neural Networks, and Hybrid models in terms of prediction accuracy, usability, and system efficiency. The combination of Adaptive Extended Kalman Filter and Fuzzy Logic enhances the reliability and adaptability of food nutrient estimation, making it a superior choice for a Food Nutrition Advisor system (Table I).

TABLE I. SUMMARY OF ACCURACY, ERROR RATES, USABILITY SCORE AND RECOMMENDATION

Metric	Best Model	AEKFFL vs Others
Acuracy	AEKFFL (94.8%)	+1.4% over hybrid, +4.5% over NN, _6.3% over SVM, +6.8% over Fuzzy
Error Rates (MAE/RMSE)	AEFKKL (Lowest)	Reduced by 10-15%. compared to NN.SVM
Usability Score (SUS)	AEKFFL (92.1)	Highest among models
Recommendation accuracy (%)	AEKFFL (95.3)	+2.1% better than Hybrid, _4.3% better than NN

V. DISCUSSIONS

The proposed AEKFFL model demonstrates superior performance, a critical evaluation should consider its computational complexity and generalizability. High accuracy alone does not guarantee robustness across different datasets or real-world scenarios. Future research should explore how AEKFFL performs under various conditions and whether it requires extensive computational resources compared to simpler models. Additionally, despite being slightly less effective, the hybrid approach may offer a better balance between performance and interpretability, making it a viable alternative in applications where computational efficiency is a concern. Thus, from Fig. 3, the AEKFFL model outperforms all baseline models with the highest accuracy (94.8%) and the lowest error rates (MAE and RMSE). This is because the adaptive nature of Kalman Filtering improves noise reduction, and the Fuzzy Logic adaptation enhances decision-making based on uncertainties in nutrition prediction proceedings.

According to Fig. 4, despite AEKFFL's superior performance, its complexity and computational efficiency should be critically examined. High accuracy does not always guarantee adaptability to real-world scenarios, especially if the model is highly dependent on hyperparameter tuning or requires extensive data preprocessing. The hybrid model, while slightly less accurate, might offer a better trade-off between performance and interpretability. On the other hand, Fuzzy Logic exhibits the weakest performance (87.8% Accuracy, 85.5% Recall, 86.6% F1-score), reinforcing the idea that purely rule-based models struggle with generalization in complex datasets. SVM, although slightly better than Fuzzy Logic, still falls behind NN and Hybrid models, suggesting that while it is useful for classification, it may not be as adaptable as deep learning-based approaches. Future research should explore whether the computational costs of AEKFFL are justified by its performance gains and whether hybrid models could offer a more balanced and efficient alternative for real-world applications. The AEKFFL model has the highest Precision, Recall, and F1-score, demonstrating its ability to accurately classify nutrient levels from food data.

As illustrated in Fig. 5, despite AEKFFL’s impressive results, a critical analysis should consider the trade-offs between model complexity and practical implementation. While it achieves the best performance across all metrics, it is essential to evaluate whether its computational demands justify these gains. The hybrid model, though slightly less effective, might offer a more balanced trade-off between efficiency and interpretability. Additionally, the response time metric highlights potential usability concerns, especially for Fuzzy Logic, which is significantly slower than the other models. This suggests that while rule-based approaches may be easier to understand, they might not be well-suited for real-time applications. Future research should focus on refining hybrid approaches or optimizing AEKFFL’s efficiency to ensure scalability and real-world applicability proceedings.

Thus, AEKFFL dynamically adjusts fuzzy membership functions and Kalman filter parameters to improve accuracy in assessing a child’s nutritional status based on age, weight, activity level, and real-time dietary intake. The EKF component enhances data reliability by filtering out inconsistencies in food tracking and wearable sensor inputs, ensuring precise nutrient calculations. Performance analysis indicates that AEKFFL achieves higher accuracy in predicting dietary deficiencies, reduces data noise, and optimizes meal planning efficiency compared to standalone fuzzy logic or conventional recommendation models. The model also demonstrates faster response times for real-time food intake tracking, and improved health risk detection for obesity and malnutrition. By offering a highly adaptive, intelligent, and computationally efficient solution, AEKFFL enhances dietary personalization, optimizes nutrient balance, and supports preventive nutrition strategies, making it a superior model for children's food nutrition applications.

The following further discusses this method’s novelties, uniqueness, advantages, and its usefulness to society in this study.

A. Novelties

The study develops an AEKFFL for children's food nutrition applications, integrating adaptive fuzzy logic with a Kalman filter to enhance the accuracy and personalization of dietary recommendations. Unlike conventional nutrition tracking systems, this novel algorithm dynamically adjusts fuzzy membership functions based on real-time dietary intake, physical activity, and individual metabolic variations, ensuring a highly adaptive meal planning approach. The Kalman filter component refines nutritional data by filtering out inaccuracies from food intake tracking and wearable health sensors, leading to precise nutrient estimations and reducing data noise. Additionally, AEKFFL incorporates a self-learning mechanism, continuously updating dietary recommendations based on historical eating patterns and real-time consumption behavior. AEKFFL significantly improves dietary balance, optimizes meal recommendations, and supports preventive nutrition strategies for children's health and well-being.

B. Uniqueness

The uniqueness of the AEKFFL in the children's food nutrition application lies in its dynamic integration of adaptive fuzzy logic with a Kalman filter, setting it apart from the existing models reviewed in the literature. Unlike traditional nutrition recommendation systems that rely on static rule-based or machine-learning models, this novel approach continuously refines dietary recommendations by adapting fuzzy membership functions based on real-time dietary intake, physical activity, and metabolic variations. The Kalman filter component enhances data reliability by filtering out inaccuracies in food tracking and wearable sensor inputs, ensuring precise nutrient estimation and intake monitoring. Additionally, unlike conventional models that offer generalized nutrition plans, AEKFFL employs a self-learning mechanism that updates dietary recommendations over time based on historical consumption patterns. Optimized for mobile health applications and IoT-based tracking, the model provides real-time, personalized meal planning, making it superior in accuracy, adaptability, and real-world applicability compared to the models discussed in the literature review.

C. Advantages

The AEKFFL offers several advantages in children's food nutrition applications by combining adaptive fuzzy logic with a Kalman filter to enhance the accuracy, personalization, and real-time adaptability of dietary recommendations. It improves nutritional accuracy by dynamically adjusting meal plans based on real-time food intake, physical activity, and metabolic variations, ensuring a personalized approach tailored to each child's needs. The Kalman filter component enhances data reliability by filtering out inaccuracies in food tracking and wearable sensor inputs, reducing errors in nutrient estimation. Additionally, its self-learning mechanism continuously updates recommendations by analyzing historical eating patterns, improving long-term dietary balance, and optimizing meal suggestions. Unlike traditional static nutrition models, AEKFFL provides real-time dietary feedback, enabling early detection of malnutrition, obesity risks, and nutrient deficiencies. It is also computationally efficient and seamlessly integrates with mobile health applications and IoT-based tracking systems, making it a scalable, adaptive, and intelligent solution for improving children's nutrition and overall well-being.

D. Usefulness to Society

The AEKFFL is highly beneficial to society as it promotes personalized, data-driven nutrition management for children, addressing key public health concerns such as malnutrition, obesity, and dietary deficiencies. By integrating real-time food tracking, wearable health monitoring, and adaptive AI-driven recommendations it empowers parents, caregivers, and healthcare professionals to ensure children receive balanced and optimal nutrition tailored to their individual needs. The model's ability to provide early detection of nutritional imbalances enables proactive intervention, reducing the long-term risks of diet-related diseases such as diabetes and cardiovascular issues. Furthermore, its seamless integration with mobile applications and IoT devices enhances accessibility and scalability, making it a valuable tool for schools, healthcare systems, and government nutrition programs. By offering a smart, automated, and adaptive solution, AEKFFL contributes to improving public health, reducing healthcare costs, and fostering a healthier future generation with better eating habits and enhanced well-being.

VI. Conclusion and Future Work

This paper addresses the challenge of improving food nutrition advisory systems, particularly for preventing obesity in children under five. Existing models struggle with parameter estimation, real-time adaptability, and accuracy in food nutrition recommendations. Traditional fuzzy logic models, while useful, often fail to adapt to evolving dietary needs, leading to suboptimal performance. To address these limitations, the study proposes the Adaptive Extended Kalman Filter Fuzzy Logic (AEKFFL) model, which integrates the Extended Kalman Filter (EKF) for dynamic estimation of nutritional values and Fuzzy Logic for adaptive decision-making. The research follows a Design Science Research Methodology (DSRM), utilizing stakeholder interviews and data sources like food composition databases, user reviews, and ingredient information. The AEKFFL model is tested against other approaches, including Fuzzy Logic, Support Vector Machine (SVM), Neural Networks (NN), and a Hybrid Fuzzy-NN model. Experimental results show that AEKFFL outperforms all baseline models, achieving 94.8% accuracy, the lowest error rates (MAE = 0.031, RMSE = 0.045), and superior usability (SUS score = 92.1%). Additionally, it provides highly precise nutrition classification (F1-score = 94.4%) and faster response times. These findings highlight AEKFFL's potential as an efficient and accurate food nutrition advisor system. Future research will focus on enhancing adaptability, integrating real-time IoT data, and improving computational efficiency for even more precise nutrition recommendations.

Acknowledgment

We would like to thank Universiti Teknikal Malaysia Melaka (UTeM) and the Ministry of Higher Education for the fundamental grant number FRGS/1/2024/ICT02/UTEM/02/12 as well as Fakulti Teknologi Maklumat dan Komunikasi (FTMK) for their support.

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