2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Artificial Neural Network for Identification of Infant Feeding Tracking Using the Smart Bottle System

Jiajun Guan, Robert Brewster, Javier de la Fuente, Ph.D., IDSA, Alison K. Ventura, Ph.D., CLEC, and Benjamin G. Hawkins, Ph.D., *Member, IEEE*

Abstract— **In this work, we present the results of a comparison of simple artificial neural network (FFNN) designs intended to identify infant bottle-feeding events and appropriate feeding volume recording intervals using accelerometer data recorded from a custom designed "Smart Bottle" system. To properly identify and distinguish these events with an accuracy of 99.8%, while accommodating the constraints of the deployment environment, two concurrent FFNNs were implemented.**

***Clinical Relevance*— Infant feeding patterns are highly correlated with obesity in adulthood; the Smart Bottle system presents an opportunity to collect accurate data with minimal disruption to the feeding interaction.**

I. Introduction and Background

A. Infant Feeding Behavior and Impacts

Rapid weight gain during infancy is a significant predictor of risk for later obesity and metabolic comorbidities [1]. One of the earliest modifiable contributors to rapid weight gain is overfeeding during bottle-feeding. Compared to infants fed directly from the breast, infants fed by bottle gain an excess of 70-90 grams/month across the first year postpartum and have higher weight status by age 2 years [2] [3] [4] . Observational research suggests both how much and how often bottle-fed infants are fed are associated with overfeeding and excess weight gain [5] [6] [7] [8]; thus, accurate measurement of feed volume and frequency are important outcome measures for interventions aimed at reducing risk for overfeeding during bottle-feeding.

B. Data Collection on Feeding Events

The current gold standard for assessing infant intake in research and clinical settings involves weighing the infant before and after each feeding within a controlled laboratory or clinical setting. While effective, it is difficult to collect long term data on feeding patterns using this method, and these settings may alter infant feeding behaviors. An alternative approach is to ask parents to keep detailed feeding diaries. Although more feasible for longer-term tracking of infant dietary patterns, this approach imposes significant participant burden since young infants typically feed between 8-12 times per day and often feed at times when parents' cognitive capacity may be limited, such as in the middle of the night or while caring for other children. Indeed, missed recordings and errors in recording are common and parent-reported feeding records tend to overestimate infant intakes by 10-23% [9] [10] [11] [12].

Figure 1: Smart Bottle system in use during simulated feeding event. The black base attached to the bottle contains sensor hardware and microcontroller for data acquisition.

Recently, specifically-designed, research-grade bottle systems have been developed to automatically record feeding data [13] [14], but these tools are limited because they specifically focus on objective measurement of infant sucking, do not provide additional data on feed volume, and may negatively impact feeding interactions because dyads are required to use unfamiliar bottles and nipples for assessment. One possible approach to address these methodological limitations is to develop an electronic device that could attach to a variety of bottles, achieving remote recording of experimental data without altering the feeding interaction.

C. The "Smart Bottle" Approach

We have developed such a system to record feeding times, volumes, and other data using a microcontroller-controlled sensor array and enclosure that attaches to the base of an infant bottle (Figure 1). The details of the "Smart Bottle" device hardware are not discussed here, but as part of the data-collection algorithm it is necessary to identify two key states: i) feeding state, when the bottle is being used, and ii) post-feeding state, when the bottle has been set down and formula volume data should be recorded.

D. Artificial Neural Network

We report the development of an artificial neural network (FFNN) algorithm to interpret "real-time" data from sensors in

J. Guan, R. Brewster, J. de la Fuente, A. Ventura, and B. G. Hawkins are with the California Polytechnic State University, San Luis Obispo, San Luis Obispo, CA 93407 (phone: 805-756-6203, email: bghawkin@calpoly.edu)

a Smart Bottle device attached to an infant bottle. The FFNN approach was chosen as the best approach to analyze data from multiple sensor sources and classify the bottle state as either “feeding” or resting “on [a] table.”

An FFNN is an algorithm consisting of one or more weighted input values ($w_i x_i$) and biases (b) that are evaluated using an activation function (φ) at a particular node as shown in 1

$$Out = \varphi(\sum_i w_i x_i + b) \quad (1)$$

Nodes are arranged in layers that are evaluated sequentially. Output from nodes in each layer are fed forward into the next layer, adding complexity to the FFNN model. Determination of the weighting factors for each input, and for the feedforward between each layer is achieved using a training algorithm and multiple training datasets. There are many such techniques; here we use the Levenberg-Marquardt technique to perform non-linear least squares regression analysis to determine weighting factors and biases. After training, the determined weights can be implemented in the final network.

The development of the FFNN algorithm for classification of “feeding” and “resting” events must operate within the constraints of the microcontroller (ATMega 32u4) environment which is limited to 32KB program variable space and 20Hz data acquisition rate. Future work will improve upon these constraints.

II. Methods

A. Sensor Data

The Smart Bottle system collects data from a number of sensors enclosed in the bottle attachment base. For this work, however, we only consider the accelerometer data for x-, y-, and z-axis acceleration and pitch, yaw, and roll gyroscope data. Data are polled and collected at 50ms intervals and stored for analysis. 5 experiments were conducted to collect data from trained lab assistants performing a simulated feeding. Supplementary training and testing data for the “resting” state was generated using MATLAB. Data at each time-point constituted a separate “dataset” for the purposes of FFNN training

B. Video Data

In addition to acceleration and gyroscope data, video recordings were collected and time-synced to each feeding simulation. These data were manually classified for training and error testing purposes. Three unique states were used: “0” for indeterminate state, “1” for “resting” or “on-table”, and “2” for “feeding.”

C. Simulated Feeding Events

To develop accurate training and test datasets, feeding events were simulated by a trained researcher. During the five simulated feedings, the researcher conducted typical activities surrounding feeding events like preparing formula, feeding, bouncing, resting, walking, and repositioning multiple times. Events were repeated with the system in different orientations to simulate normal variability across the range of feeding events.

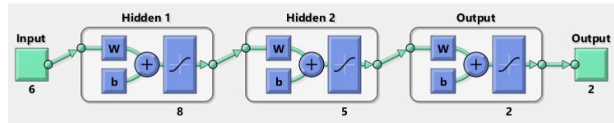
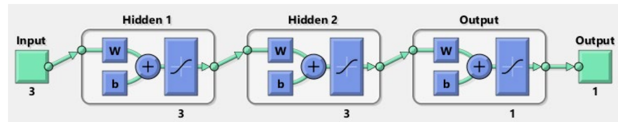
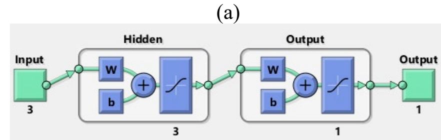


Figure 2: FFNN structure for Model 1. 6 inputs and 2 hidden layers are used to produce 2 potential outputs.

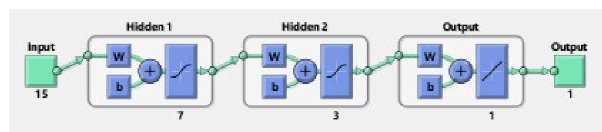


(a)

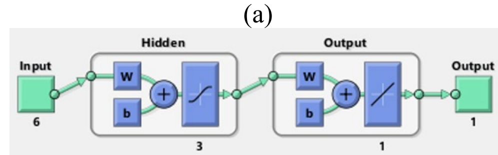


(b)

Figure 3: FFNN structure for Model 2. (a) 3 inputs and 2 hidden layers are used to produce 1 output for “feeding.” (b) 3 inputs and 1 hidden layer are used to produce 1 output for “on-table.”



(a)



(b)

Figure 4: FFNN structure for Model 3. (a) 15 inputs and 2 hidden layers are used to produce 1 output for “feeding.” (b) 6 inputs and 1 hidden layer are used to produce 1 output for “on-table.”

D. Model and Data Analysis

MATLAB was used for FFNN development, training, testing, and data analysis. The Deep Learning Toolbox provides a UI for developing FFNN models, applying training data, and data analysis.

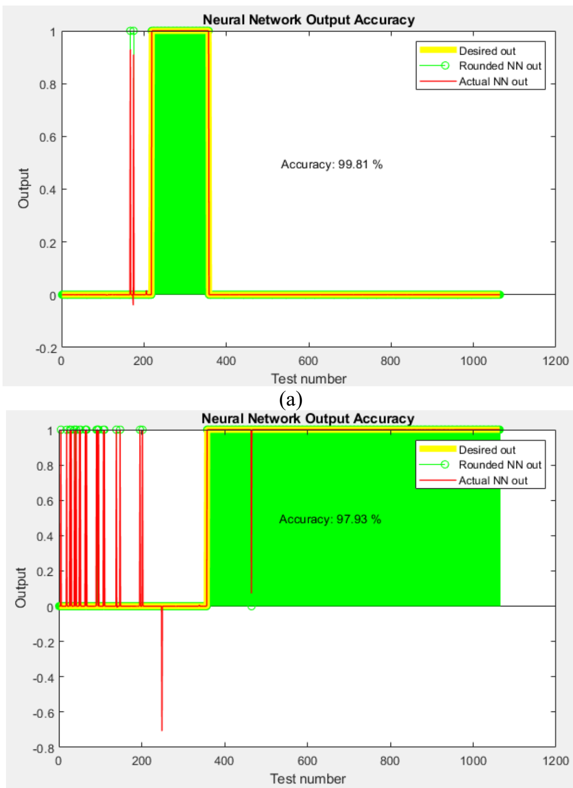
E. FFNN Models

Three FFNN models were implemented to test for key weighting factors. The first model (Model 1) used all six datapoints (x-, y-, and z-axis acceleration and pitch, yaw, and roll gyroscope data) and produced two outputs (“feeding” and “on-table”) using two hidden network layers and 1 output layer, as shown in Figure 2. A second model (Model 2) was used to evaluate the relative contributions of acceleration (x, y, z) and gyroscope (p,y,r) data to each of the two outputs. In this mode, FFNNs were developed for three inputs and a single output, to independently identify “feeding” and “on-table” events. The “feeding” FFNN used two hidden layers and 1 output layer while the “on-table” FFNN used one hidden layer and one output layer, as shown in Figure 3. The final model uses only the accelerometer inputs, but includes the five most recent measurements of each, resulting in 15 inputs used to classify two outputs using two hidden layers and 1 output layer, as shown in

Figure 4. Two FFNNs are trained using this model, for "feeding" and "on-table", respectively, and the "on-table" output is delayed until 15 consecutive outputs are captured.

F. FFNN Training

Five simulated feeding events were recorded using the Smart Bottle system with simultaneous recorded video. Time-stamped accelerometer and gyroscope data were aligned with video and manually classified as "feeding," "on-table," or neither. Four of the datasets were used as training sets and the fifth was reserved for testing. The testing and training datasets were cycled throughout model development. Additional training data was generated for the "on-table" events using Gaussian distributed random variables classified within a 2% threshold of expected "on-table" values. Additional testing data was also generated using uniformly distributed random variables. This data was used only in Model 2 to train and evaluate the "on-table" FFNN accuracy.



(a)

(b)

Figure 5: Model 1 "feeding" and "on-table" accuracy. Red and green lines indicate FFNN output (raw and rounded) and yellow is the desired output.

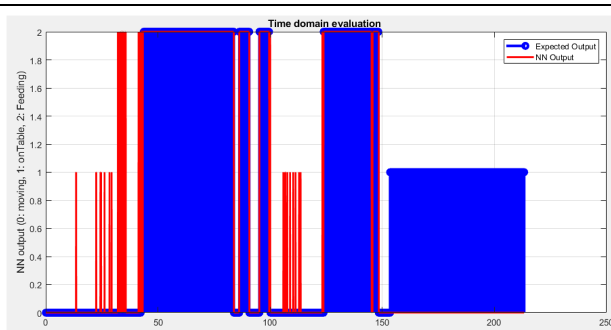


Figure 7: Model 1 combined output data for simulated feeding events. 2 indicates "feeding," 1 indicates "on-table," and 0 indicates neither. Note the significant error after 150 seconds.

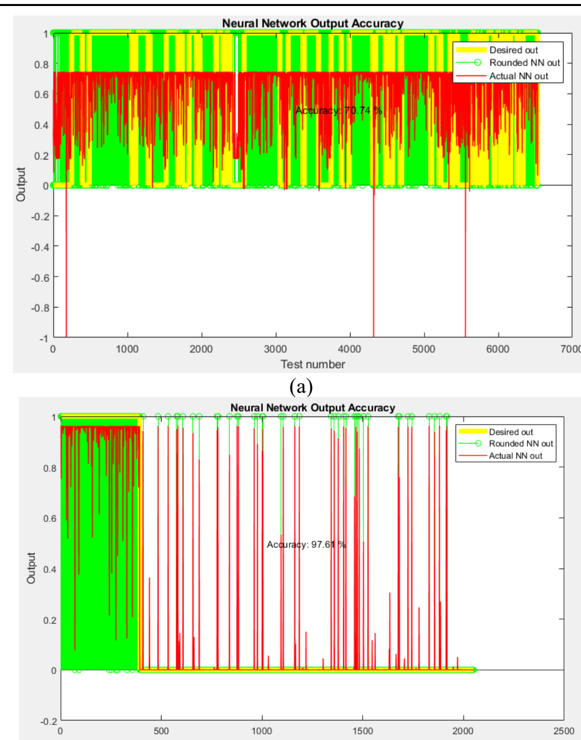
III. Results and Discussion

A. Model 1: 6-input, 2-output

Initially, we designed a single FFNN to identify both possible events based on the instantaneous values of the accelerometer and gyroscope. This 6-input, 2-output model was trained and tested using data from four of the five simulated feedings. The results (shown in Figure 6) indicate that the independent accuracies are 99.8% and 97.9% for "feeding" and "on-table," respectively. However, combined evaluation method and significant overlap of datapoints for each event mean that the overall accuracy is significantly lower, as shown in Figure 9 where a significant portion of "on-table" data was not identified by the FFNN.

B. Model 2: 3-input, 1-output (2 parallel FFNN)

The relative contributions of accelerometer and gyroscope data to each output, separate parallel FFNNs were trained and tested. The accuracy of gyroscope data in predicting "feeding" was 70.7% and "on-table" was 97.8%. The accelerometer-only FFNN maintained accurate output, correctly identifying 99.3% and 99.8% of "feeding" and "on-table" events, respectively. The results, shown in Figure 8, indicate that the gyroscope data contributes negligibly to the FFNN "feeding" output and can be omitted.



(a)

(b)

Figure 6: Model 2 "feeding" and "on-table" accuracy using only pitch, yaw, and roll gyroscope data. Red and green lines indicate FFNN output (raw and rounded) and yellow is the desired output.

C. *Model 3: 15-input, 1-output (2 parallel FFNN)*

Using only accelerometer data allowed for greater flexibility in the size of the input dataset. Given the restrictions on programming and variable space, only a limited number of inputs could be used, and the data indicated a need for incorporating movement history in addition to instantaneous data. To do this, the most recent five datapoints for x-, y-, and z-axis acceleration were included as inputs (the maximum allowed given space constraints). Using this model, the FFNN achieved 99.7% accuracy in identifying "feeding" events with a 0.125 second group delay, as shown in Figure 7, but continued to misidentify "on-table" events. Adding an accumulator to identify 15 consecutive "on-table" outputs, effectively delaying the output by 0.75 seconds, corrected the error, as shown in Figure 10.

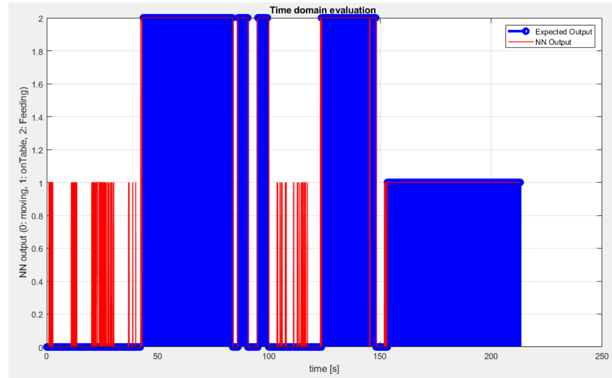


Figure 8: Model 3 combined output data for simulated feeding events. 2 indicates "feeding," 1 indicates "on-table," and 0 indicates neither.

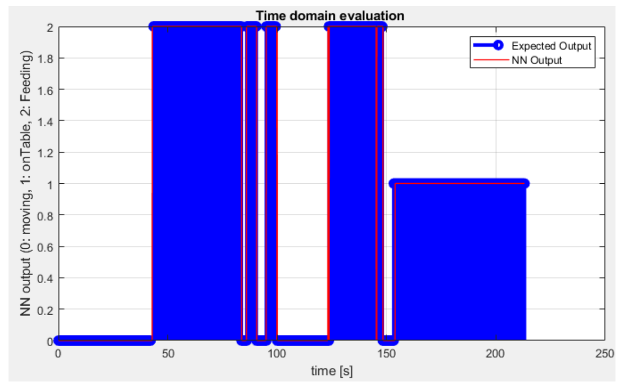
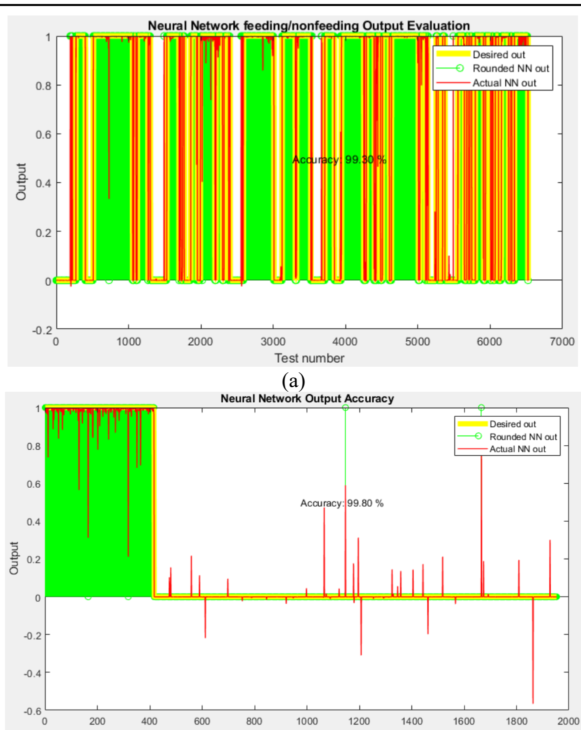


Figure 9: Model 3 combined output data for simulated feeding events using a 15-point accumulator for "on-table" events.

IV. Conclusion

The ability to identify feeding events during data acquisition for tracking infant bottle-feeding behaviors in a flexible setting is an essential part of tracking such behaviors without affecting the subject's environment. The development of an adaptable sensor hardware interface along with algorithmic event identification enables *in-situ* accurate data collection in an easily deployable manner. The critical adaptation presented here is the inclusion of time-history data in the FFNN training and testing sets for identification of "feeding" events, the identification of gyroscope data as unnecessary for identification of "feeding" events, and the inclusion of a 15-count accumulator for "on-table" data that corrects for momentary events that match test data while reducing computational overhead in the FFNN algorithm. Given the wide-spread usage of bottles for infant feeding, this intake-tracking device holds the potential to improve assessment of infant feeding patterns, a critical foundation for obesity prevention efforts.



(a)

(b)

Figure 10: Model 2 "feeding" and "on-table" accuracy using only x-, y-, and z- axis accelerometer data. Red and green lines indicate FFNN output (raw and rounded) and yellow is the desired output

Acknowledgment

The authors gratefully acknowledge the support and efforts of AKV's student, M. L. Treiber; BGH's students J. Carroll, E. Zien, J. Dirksen, N. Nyberg; and JdlF's students A. Lopez, K. Martinez, J. McKeag, C. Miller, and K. Young.

V. References

[1] M. Zheng, K. E. Lamb, C. Grimes, R. Laws, K. Bolton, K. K. Ong and K. Campbell, "Rapid weight gain during infancy and subsequent adiposity: a systematic review and meta-analysis of evidence," *Obes Rev.,* vol. 19, no. 3, pp. 321-332, March 2018.

[2] M. J. Heinig, K. G. Dewey, L. A. Nommsen, J. M. Peerson and B. Lonnerdal, "Growth of breast-fed and formula-fed infants from 0 to 18 months: the DARLING Study," *Pediatrics,* vol. 89, no. 6 Pt 1, pp. 1035-41, 1992.

[3] A. K. Ventura, "Developmental Trajectories of Bottle-Feeding During Infancy and Their Association with

Weight Gain," *J Dev Behav Pediatr,* vol. 38, no. 2, pp. 109-119, 2017.

[4] R. Li, J. Magadia, S. B. Fein and L. M. Grummer-Strawn, "Risk of bottle-feeding for rapid weight gain during the first year of life," *Arch Pediatr Adolesc Med,* vol. 166, no. 5, pp. 431-6, May 2012.

[5] S. Mihrshahi, D. Battistutta, A. Magarey and L. A. Daniels, "Determinants of rapid weight gain during infancy: baseline results from the NOURISH randomised controlled trial," *BMC Pediatrics,* vol. 11, p. 99, 2011.

[6] C. T. Wood, A. C. Skinner, H. S. Yin, R. L. Rothman and E. M. Perrin, "Association Between Bottle Size and Formula Intake in 2 Month Old Infants," *Acad Pediatr.,* vol. 16, no. 3, pp. 254-259, Apr 2016.

[7] C. T. Wood, A. C. Skinner, H. S. Yin, R. L. Rothman, L. M. Sanders, A. M. Delamater and E. M. Perrin, "Bottle Size and Weight Gain in Formula-Fed Infants," *Pediatrics,* vol. 138, no. 1, 2016.

[8] J. Worobey, M. I. Lopez and D. J. Hoffman, "Maternal behavior and infant weight gain in the first year," *J Nutr Educ Behav,* vol. 41, no. 3, pp. 169-75, May-Jun 2009.

[9] J. O. Fisher, N. F. Butte, P. M. Mendoza, T. A. Wilson, E. A. Hodges, K. C. Reidy and D. Deming, "Overestimation of infant and toddler energy intake by 24-h recall compared with weighed food records," *Am J Clin Nutr,* vol. 88, no. 2, pp. 407-15, 2008.

[10] B. Devaney, P. Ziegler, S. Pac, V. Karwe and S. I. Barr, "Nutrient intakes of infants and toddlers," *J Am Diet Assoc,* vol. 104, no. 1 Suppl 1, pp. 14-21, 2004.

[11] B. Devaney, M. Kim, A. Carriquiry and G. Camano-Garcia, "Assessing the Nutrient Intakesof Vulnerable Subgroups," USDA, Economic Research Service, Washington, 2005.

[12] K. M. Hurley, M. M. Black, B. C. Merry and L. E. Caulfield, "Maternal mental health and infant dietary patterns in a statewide sample of Maryland WIC participants," *Matern Child Nutr,* vol. 11, no. 2, pp. 229-39, 2015.

[13] E. Sazonov, M. H. Imtiaz, J. Bahorski, C. R. Schneider and P. Chandler-Laney, "Design and Testing of an Instrumented Infant Feeding Bottle," *IEEE Sensors,* pp. 1-4, October 2018.

[14] G. J. Capilouto, T. J. Cunningham, D. R. Mullineaux, E. Tamilia, C. Papadelis and P. J. Giannone, "Quantifying neonatal sucking performance: promise of new methods," *Semin. Speech Lang,* vol. 38, no. 2, pp. 147-158, 2017.