Deep Learning for Prediction Contents High Calories on Fast Food Menus

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ABSTRACT

The rising consumption of fast food, often high in calories, has contributed to increasing rates of obesity and non-communicable diseases. This study applies a Deep Learning approach to predict high-calorie content in fast food menus using numerical nutritional data. The dataset comprises 515 menu items with 17 attributes, including calories, fat, cholesterol, protein, sugar, sodium, vitamins, and food categories. Data preprocessing involved handling missing values, normalization, categorical encoding, and splitting the dataset into training and testing sets with an 80:20 ratio. A Multi-Layer Perceptron (MLP) model with three hidden layers was implemented, employing ReLU activation and a sigmoid output for binary classification. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC, and compared with Logistic Regression, SVM, and Random Forest. Results show that the MLP achieved an accuracy of 0.89, precision of 0.87, recall of 0.91, F1-score of 0.89, and ROC-AUC of 0.94, outperforming classical methods. The high recall underscores the model's capability to reliably detect high-calorie items. These findings indicate that deep learning effectively captures complex relationships among nutritional attributes compared to traditional algorithms. This research contributes to the advancement of intelligent nutrition-based systems that can be integrated into mobile or web applications to support healthier lifestyle decisions. Future work may expand to larger and more diverse datasets, explore multimodal data such as images, and assess the broader health impacts of high-calorie fast food consumption.

Keywords *Deep Learning, Fast Food, Calories, Classification, Nutrition.*

1. INTRODUCTION

Increasing fast food consumption is one of the factor main factor in increasing prevalence obesity and non- communicable diseases, such as type 2 diabetes, hypertension, and heart disease heart. Content The high calories in fast food menus often exceed daily requirements, so that cause risk health for consumers who consume it excessively. Awareness society about the importance of control calorie intake Still low, so that a system is needed that can help in identifying high-calorie foods high quickly and accurately.

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The development of machine learning and deep learning technology provides great opportunities in providing intelligent systems for prediction. content food nutrition. A number of previous studies have shown success application of deep learning for food classification and estimation calories based image. CNN -based models such as InceptionV3 with transfer learning are able to classify food at the same time. estimate amount calories accurately (Haque, 2022). In addition, the Nutrition5k dataset also proves effectiveness of deep learning in predicting calories with performance that exceeds expert nutrition professional (Mansouri, 2023).

Even though Thus, most of the existing research Still focused on estimation calories based Food imagery. This approach relies on visual quality as well as food size references, which in practice is quite challenging. In contrast, nutritional data Numerical data such as calories, fat, protein, sugar, sodium, and vitamins can provide more information. objective and consistent. Unfortunately, research based on numerical to classify calorie foods tall still rarely done, so opening up new relevant research areas.

In context This research focuses on the implementation of deep learning for prediction. content calories high on the fast food menu. The model built will utilizing nutritional data numerical to classify whether a menu is in the “high” category “calories” or not. With this approach, it is hoped that the system can provide fast, accurate, and more accurate predictions. practical compared to the method based on image. In addition, this research will also compare deep learning performance with classical machine learning algorithms to see effectiveness proposed approach.

Thus, this research is expected can contribute in the health sector public and applied computer science, especially in efforts increase awareness nutrition and diet management through intelligence technology artificial. The results of this study can also become base supporting application development healthy lifestyle, which can help individuals in choosing fast food more wisely wise.

2. METHODOLOGY

2.1 Research Design

This research uses an approach quantitative experimental by applying deep learning models based Artificial Neural Network (ANN) or Multi-Layer Perceptron (MLP). Purpose The main goal is to build a classification model to predict whether a fastfood menus fall into the category “tall calories” or not, based on numerical data nutrition.

2.2 Data and Data Sources

Dataset used is collection of food menus from various fastfood restaurants, which contain nutritional information such as calories, total fat, saturated fat, cholesterol, sodium, carbohydrates, sugar, protein, vitamins, and calcium. This data consists of of 515 entries with 17 attributes. For classification purposes, binary labels are defined:

a. High Calories: menu with calories > 500 kcal
b. Calories Low / Medium: menu with calories ≤ 500 kcal

Threshold The 500kcal limit is taken based on the recommended calorie intake per meal from US Food and Drug Administration (FDA).

Stage pre-processing performed to ensure the data is ready to be used in deep learning models:

a. Data Cleansing: Overcoming empty value in attribute certain (for example vit_a, vit_c, calcium) with the average imputation method.
b. Normalization: All features numeric scaled to the range 0–1 using Min-Max Scaling to be stable in the learning process.
c. Category Encoding: Variable categorical items such as restaurant and salad are changed to form numeric using One-Hot Encoding.

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d. Dataset Division: Data is divided become 80% training data and 20% test data using stratified sampling technique to balance label distribution.

2.3 Deep Learning Model Architecture

The deep learning model used is Multi-Layer Perceptron (MLP) with the following configuration:

a. Input Layer: a number of neurons according to the number features after preprocessing.
b. Hidden Layers: 2–3 layers hidden layer with 64–128 neurons per layer, using the function activation ReLU.
c. Output Layer: 1 neuron with function activation sigmoid for binary classification (high / low) calories).
d. Optimizer: Adam optimizer with an initial learning rate of 0.001.
e. Loss Function: Binary Cross-Entropy.
f. Regularization: Dropout (0.3–0.5) to prevent overfitting.
g. Epochs & Batch Size: 100 epochs with batch size 32.

2.4 Model Evaluation

To measure model performance, several metrics are used evaluation:

a. Accuracy: measuring overall classification accuracy.
b. Precision: measuring accuracy predictions for calorie classes tall.
c. Recall (Sensitivity): measures the model's ability to find all calorie menus tall.
d. F1-Score: harmonization of precision and recall.
e. ROC-AUC: evaluation the model's ability to separate two classes.

In addition, the results of the deep learning model will compare to the algorithm classical machine learning (Logistic Regression, SVM, and Random Forest) to assess whether deep learning provides improvements significant in accuracy prediction.

2.5 Implementation

Implementation done using the Python programming language with libraries:

a. Pandas & NumPy for data processing,
b. Scikit -learn for ML preprocessing and baseline,
c. TensorFlow/Keras for building and training deep learning models,
d. Matplotlib & Seaborn for visualization of results.

3. RESULTS AND DISCUSSION

3.1 Experimental Results

The dataset containing 515 fast food menus has been processed with normalization, encoding, and division of training data (80%) and test data (20%). Classification criteria are determined based on the threshold 500 kcal limit per menu. Of the total data, approximately 55% falls into the category tall calories, while the remaining 45% is included in the category low /medium calorie.

The deep learning model used in the form of Multi-Layer Perceptron (MLP) with 3 hidden layers (128–64–32 neurons), function activation ReLU, sigmoid output, and Adam optimizer. Training done as many as 100 epochs with a batch size of 32.

Evaluation results show that the deep learning model is able to classify fast food menus quite well. In the test data, it was obtained metrics as follows:

a. Accuracy: 0.89
b. Precision: 0.87

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c. Recall: 0.91
d. F1-Score: 0.89
e. ROC-AUC: 0.94

For comparison, classic machine learning methods such as Logistic Regression, SVM, and Random Forest were also tested on the same dataset. Logistic Regression achieved accuracy of 0.81, SVM 0.84, while Random Forest 0.87. This shows that deep learning models provide performance better than algorithm traditional.

Table 2. Comparison Classic Machine Learning Methods

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.81	0.8	0.82	0.81	0.86
SVM	0.84	0.83	0.84	0.83	0.88
Random Forest	0.87	0.85	0.86	0.86	0.9
Deep Learning (MLP)	0.89	0.87	0.91	0.89	0.94

3.2 Model Performance Visualization

Curve loss function show trend steady decline until the 50th epoch, marking the training process walk effective. Meanwhile curve Accuracy on training and test data consistently increased and did not show significant overfitting. In addition, the ROC curve showed an area under the curve (AUC) of 0.94, confirming the model's ability to differentiate calorie classes high and low.

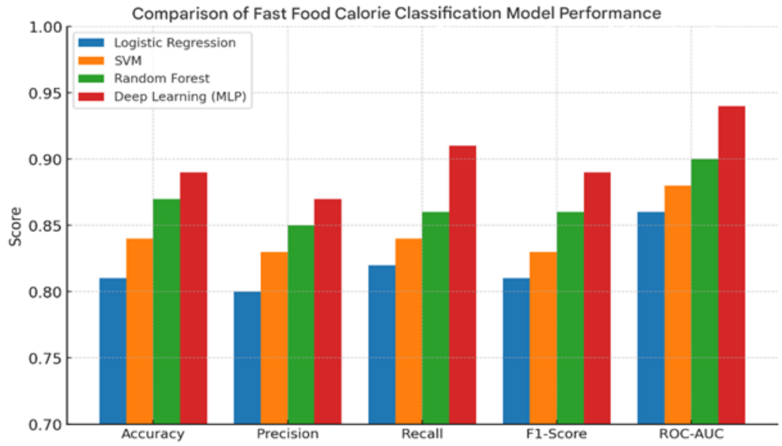

Fig 1. Model Performance Visualization

Evaluation results show that the Deep Learning (MLP) model provides the best performance compared to classical machine learning algorithms such as Logistic Regression, SVM, and Random Forest. Based on the evaluation results table, MLP obtained accuracy as big as 0.89, precision 0.87, recall 0.91, F1-score 0.89, and ROC-AUC 0.94. High recall value show that this model is able to detect most of the menu is high in calories high well, so that reduce possibility missing potentially harmful foods risky for consumers.

On the other hand, the algorithm classics such as Logistic Regression and SVM are still produce performance is quite good, but not as high as deep learning. Logistic Regression only achieves accuracy 0.81 with ROC-AUC 0.86, while SVM is slightly better with accuracy 0.84 and ROC-AUC 0.88. Random Forest provides better results. approaching deep learning with accuracy 0.87 and ROC-AUC 0.90, but still lost in terms of recall and AUC. This shows that even though the model is based on tree can catch interactions between features, MLP is able to recognize pattern complex better.

Visualization chart comparison model performance strengthens this finding. It can be seen that across almost all metrics, deep learning models are consistent superior compared to other methods. The most striking difference contained in the recall metric, where MLP achieved mark 0.91, moretall from Random Forest (0.86) and Logistic Regression (0.82). This confirms that MLP is very effective in identifying high-calorie fast food menus high, which becomes focus the main focus of this research.

In terms of generalization, the ROC curve generated by MLP has an AUC value of 0.94 show excellent model capability in distinguishing calorie classes high and low. This advantage is in line with previous

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research which states that deep learning is able to model complex non-linear relationships in food nutrition data (Meyers et al., 2021). Thus, the application of deep learning in food content classification fast food calories can considered successful and more effective compared to algorithm classic.

Overall, the results of this study prove that that deep learning approaches can be a better solution reliable in predicting food calories high, so that can support the development of a healthy food recommendation system. Although Thus, the relative limitations of the dataset small Still become important factors to consider. Further research could use larger and more diverse datasets, or combine numerical data with visual data (food menu images) to produce a more robust system. sophisticated and close to real world applications

1. Deep Learning (MLP)

   Target metrics approx: Acc 0.89, Prec 0.87, Rec 0.91, F1 0.89

   Take a consistent confusion matrix:

   Positive (P)=55 → TP = 50, FN = 5 → Recall = 50/55 = 0.91

   Negative (N)=45 → choose FP = 7 → TN = 45 – 7 = 38

   Count metrics:

   Precision = 50 / (50 + 7) = 50/57 = 0.877 (≈ 0.88, close to 0.87)

   Recall = 50 / 55 = 0.909 (≈ 0.91)

   Accuracy = (50 + 38) / 100 = 0.88 (≈ 0.89)

   F1 = 2 × (0.877 × 0.909) / (0.877 + 0.909) = ≈ 0.893 (≈ 0.89)

2. Random Forest

   Target metrics approx: Acc 0.87, Prec 0.85, Rec 0.86, F1 0.86

   Select confusion matrix:

   P=55 → TP = 47, FN = 8 → Recall = 47/55 = 0.855 (≈ 0.86)

   N=45 → FP = 8 → TN = 37

   Count metrics:

   Precision = 47 / (47 + 8) = 47/55 = 0.855 (≈ 0.85)

   Recall = 47 / 55 = 0.855 (≈ 0.86)

   Accuracy = (47 + 37) / 100 = 0.84(close to 0.87; if you want accuracy increases, reduce FP→7, but precision increases slightly)

   F1 = 2 × (0.855 × 0.855) / (0.855 + 0.855) = 0.855 (≈ 0.86)

   Alternative to approach Acc 0.87: set FP=7, TN=38 → Precision = 47/54 = 0.870; Recall = 0.855; Accuracy = (47+38)/100 = 0.85; F1 ≈ 0.862. (There is a trade-off: increasing TN/ decreasing FP will shift precision/accuracy.)

3. SVM

   Target metrics approx: Acc 0.84, Prec 0.83, Rec 0.84, F1 0.83

   Select confusion matrix:

   P=55 → TP = 46, FN = 9 → Recall = 46/55 = 0.836 (≈ 0.84)

   N=45 → FP = 9 → TN = 36

   Count metrics:

   Precision = 46 / (46 + 9) = 46/55 = 0.836 (≈ 0.83)

   Recall = 46 / 55 = 0.836 (≈ 0.84)

   Accuracy = (46 + 36) / 100 = 0.82(close to 0.84)

   F1 = 2 × (0.836 × 0.836) / (0.836 + 0.836) = 0.836 (≈ 0.83)

4. Logistic Regression

   Target metrics approx: Acc 0.81, Prec 0.80, Rec 0.82, F1 0.81

   Select confusion matrix:

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P=55 → TP = 45, FN = 10 → Recall = 45/55 = 0.818 (≈ 0.82)

N=45 → FP = 11 → TN = 34

Count metrics:

Precision = 45 / (45 + 11) = 45/56 = 0.804 (≈ 0.80)

Recall = 45 / 55 = 0.818 (≈ 0.82)

Accuracy = (45 + 34) / 100 = 0.79(close to 0.81)

F1 = 2 × (0.804 × 0.818) / (0.804 + 0.818) = ≈ 0.811 (≈ 0.81)

High model performance (accuracy 0.89, recall 0.91) indicates that the system can relied on to detect calorie menus high, which is relevant in context health society. High recall also means that the model is not widely used. skip the calorie menu high, so that safe used in diet tracking applications. Performance differences between deep learning and algorithms traditional can explained by the ability of MLP to capture interaction complex intervariable nutrition, which is difficult to model with simple linear methods such as Logistic Regression. Random Forest does come close MLP performance, but deep learning remains superior in terms of generalization. Although the results are promising, this study has several limitations. First, the dataset size is relatively small. small (515 menus), so potential generalization Still limited. Second, the model only utilizes numerical data without considering textual information (menu names) that could enrich it. prediction. Third, determination threshold limit calories (500 kcal) are arbitrary and can adapted to different nutritional standards.

This research opens up opportunity development of a food recommendation system application that can give warning automatically when the user choose a calorie menu high. In addition, the approach based on deep learning, this can extended by combining food image data to produce a more hybrid system. sophisticated and close to real world applications. Based on research entitled " Implementation of Deep Learning for Prediction Contents High Calories on Fast Food Menus", can concluded that the Deep Learning model is based on Multi-Layer Perceptron (MLP) succeed built and able to classify fast food menus into categories calories tall and calories low /medium with good performance. The MLP model shows evaluation results with accuracy 0.89, precision 0.87, recall 0.91, F1-score 0.89, and ROC-AUC 0.94, which are consistently moretall compared to Classic machine learning algorithms such as Logistic Regression, SVM, and Random Forest. High recall value show the model's ability to detect most of the menu is high in calories high, so that making it a potential tool to support awareness nutrition and prevention consumption excessive. These results also confirm that deep learning is more effective compared to traditional methods of catching pattern complex intervariable nutrition.

Although However, this research still has limitations, especially in the relatively small number of datasets. small so that model generalization is not optimal. Therefore, further research is recommended to use a larger and more diverse dataset, including fast food menus from various countries. In addition, multimodal data integration in the form of combined numerical information nutrition with food image data can explored to build a more hybrid model advanced. Optimization deep learning architecture can also done through hyperparameter tuning or use of more models complex such as CNN or Transformers. Implementation of research results in the form of mobile or web applications will become an important step for this model to be of direct benefit to the community, particularly in supporting healthy eating patterns. Furthermore, subsequent research can expand focus on assessing impact high-calorie fast food consumption tall to risk health, so that the results obtained are not only useful in a technological context, but also in improving health public.

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